THE DEVELOPMENT AND EMPIRICAL EVALUATION OF A CLIENT/INVESTOR RISK-TOLERANCE MODEL

by
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DECLARATION

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ABSTRACT

Risk-Tolerance is an influential individual differences factor that determines the composition of financial portfolios that are optimal regarding the risk and return for the investor. At the heart of the financial services sector lie competent financial advisors. The foundation of any financial plan requires a thorough assessment of the *Risk-Tolerance* of the client/investor. Relying primarily on demographic and socioeconomic factors as predictors of *Risk-Tolerance* could undermine the ability of the financial advisor to accurately gauge the baseline degree of *Client Risk-Tolerance*. This may lead to wrongfully matching a client's objectives with the financial plan, which could result in various costly effects. The successful advisor is one who realises that an understanding of the individual he/she is dealing with is just as important as a thorough understanding of the technical aspects of investments and the basic nature of investment decision-making. However, since there is no neatly packaged one-size fits all product, the service remains largely dynamic in nature – one that needs due consideration to each individual investor's personal circumstances and preferences. It is argued that the most prudent approach to delivering sound investment advice would rely on the financial advisor's ability to assess and integrate two distinct sets of data pertaining to overall *Client/Investor Risk-Tolerance*, that is, the combination of the client's *objective risk-tolerance* (i.e. selected demographic and socioeconomic variables) as well as his/her *subjective risk judgment* (i.e. selected personality and emotion regulation variables) assessment. This research study aimed to determine how personality and emotional self-regulation variables (i.e. *subjective risk judgment*), as well as demographic and socioeconomic variables (i.e. *objective risk-tolerance*) could be combined in a conceptual model to differentiate amongst different levels of *Client/Investor Risk-Tolerance*.

A cross-sectional dataset (n = 205) obtained from investors seeking financial advice, was used to fit the structural model via structural equation modelling (LISREL 8.8). Interaction effects were tested with moderated regression. The questionnaire included measures of personality, emotion regulation, risk-tolerance, as well as age, gender, education level and annual income. Both the measurement model (p-value for test of close fit = .592; RMSEA = .0475, NNFI = .937, CFI = .957, SRMR = .0591) and structural model (p-value for test of close fit = .0644; RMSEA = .0621, NNFI =

.892, CFI = .919, SRMR = .0727) attained good fit. The results revealed empirical support for five of the 15 hypothesised paths contained in the structural model. More specifically, *Sensation Seeking* exerted a moderate positive direct influence on *Risk-Tolerance*. This result supported the argument that individuals with higher levels of self-reported *Sensation Seeking*, seeking financially risky experiences and stimulation by definition, will appraise risk as less threatening and anticipate arousal as more positive than their lower *Sensation Seeking* counterparts. The results further provided insight into the complexity of the dynamics underlying the different personality and emotion regulation variables contained in the model. For example, *Extraversion* was found to positively influence *Sensation Seeking*. This finding is in support of the notion that extraverts seek situations that provide them with higher levels of stimulation in order to maintain optimal levels of cortical arousal. Research has shown that extraverts are habitually in a state of lower cortical arousal, when compared to introverts. They tend to have higher sensory thresholds, and thus have smaller reactions to sensory stimulation, leading them to seek more thereof. Furthermore, *Conscientiousness* was found to positively influence *Delay of Gratification*. Consequently, it can be inferred that individuals who are strong willed, cautious and planful with a strong sense of self-discipline will naturally more likely display a superior ability to forego immediate gratification, in pursuit of achieving something of greater enjoyment or value at a future point in time. Further to this, the results revealed that *Extraversion* and *Neuroticism* exerted significant influences on *Emotional Self-Management*. Hence, it can be concluded that *Extraversion* predicts adaptive emotion regulation strategies, where individuals exhibiting this trait display the ability to preserve or savour positive emotions (i.e. *Emotional Self-Management*). In contrast to this, the results suggested that individuals higher on *Neuroticism* will more regularly use maladaptive emotion regulation strategies, and thus make poor use of adaptive strategies to repair negative emotions, resulting in less reported *Emotional Self-Management*. The moderated regression results revealed *Gender* to be a significant moderator in the *Neuroticism – Risk-Tolerance, and Emotional Self-Management – Risk-Tolerance* relationships, respectively. Secondly, empirical support for *Income* and *Education* as moderating variables emerged, indicating that *Income* and *Education* significantly moderated the effect of *Emotional Self-Management* on *Risk-Tolerance*, respectively.

The research results provided some insights into the relevant factors that can be used to judge *Client/Investor Risk-Tolerance*. A practical implication of the results is that this information can be used to classify investors into four different client categories or profiles that are clearly distinguishable in terms of their personal characteristics. Each profile raises unique needs warranting different actions on the part of the financial advisor.

A successful financial advisor is able to transfer technical knowledge attained through comprehensive financial education into a coaching or counselling approach that enables the investor to make an investment decision that balances maximal gain (financially) with maximal security (emotionally). Investors should be encouraged to take the maximum amount of risk given their unique combination of objective and subjective characteristics. How the advisor goes about pursuing this requires an understanding of individual differences and other socio-demographic variables, and the ability to use these as a means of screening the client into the correct client category, and provide the associated supporting actions.

OPSOMMING

Risikotoleransie is 'n invloedryke faktor van individuele verskille wat die optimale samestelling van 'n finansiële portefeulje vir die betrokke belegger se risiko en opbrengs bepaal. Bevoegde finansiële raadgewers maak die kern van die finansiëledienstesektor uit. Enige finansiële plan moet berus op 'n deeglike beoordeling van die kliënt/belegger se *Risikotoleransie*. Indien daar hoofsaaklik op demografiese en sosio-ekonomiese faktore as voorspellers van *Risikotoleransie* staatgemaak word, kan dit die finansiële raadgewer se vermoë ondermyn om die basislynomvang van die kliënt se *Risikotoleransie* akkuraat te peil. Dít kan daartoe lei dat die finansiële plan nie die kliënt se oogmerke korrek weergee nie, wat die betrokkenes op verskeie maniere duur te staan kan kom. 'n Suksesvolle raadgewer is een wat besef dat 'n begrip van die individu met wie hy/sy werk ewe belangrik is as 'n begrip van beleggings. Aangesien daar egter geen enkele, netjies verpakte produk is wat vir almal werk nie, bly die diens hoofsaaklik dinamies van aard en vereis dit behoorlike inagneming van elke individuele belegger se persoonlike omstandighede en voorkeure. Daar word aangevoer dat die verstandigste benadering tot grondige beleggingsadvies berus op die finansiële raadgewer se vermoë om twee verskillende datastelle met betrekking tot algehele *Kliënt-/Beleggersrisikotoleransie* te beoordeel en te integreer, naamlik die kombinasie van die kliënt se *objektiewe risikotoleransie (*d.w.s. uitgesoekte demografiese en sosio-ekonomiese veranderlikes) en sy/haar *subjektiewe risiko-oordeel (*d.w.s. uitgesoekte veranderlikes van persoonlikheid en emosionele regulering). Die doel met die navorsingstudie was om vas te stel hoe veranderlikes van persoonlikheid en emosionele selfregulering (d.w.s. *subjektiewe risiko-oordeel*) sowel as demografiese en sosio-ekonomiese veranderlikes (d.w.s. *objektiewe risikotoleransie*) saamgevoeg kan word in 'n konseptuele model om tussen die verskillende vlakke van *Klient-/Beleggersrisikotoleransie* te onderskei.

'n Deursneedatastel (n = 205) wat verkry is van beleggers wat finansiële advies ingewin het, is gebruik om die strukturele model deur middel van strukturele vergelykingsmodellering (LISREL 8.8) te pas. Interaksie-effekte is met gemodereerde regressie getoets. Die vraelys het metings van persoonlikheid, emosionele regulering, risikotoleransie sowel as ouderdom, geslag, opvoedingsvlak en jaarlikse inkomste ingesluit.

Die metingsmodel (p-waarde vir goeiepassingstoets = .592; RMSEA = .0475, NNFI = 0.937, CFI = .957, SRMR = 0.0591) sowel as die strukturele model (p-waarde vir goeiepassingstoets = .0644; RMSEA = .0621, NNFI = .892, CFI = .919, SRMR = .0727) het 'n goeie passing opgelewer. Die resultate het empiriese steun vir vyf van die 15 veronderstelde paaie in die strukturele model opgelewer. Meer bepaald het *Die Soeke Na Sensasie ("Sensation Seeking")* 'n matige positiewe direkte invloed op *Risikotoleransie* gehad. Hierdie resultaat staaf die argument dat individue wat self erken dat hulle groot sensasiesoekers is, en dus volgens die definisie finansieel riskante ervarings en stimulasie najaag, risiko as minder bedreigend sal ervaar en opwinding in 'n meer positiewe lig sal beskou as hulle eweknieë wat minder graag sensasie najaag. Voorts het die resultate ook verdere insigte in die komplekse dinamiek onderliggend aan die verskillende veranderlikes van persoonlikheid en emosionele regulering in die model gelewer. So byvoorbeeld het *Ekstroversie ("Extraversion")* 'n positiewe invloed op *Die Soeke Na Sensasie* gehad. Hierdie bevinding ondersteun die gedagte dat ekstroverte omstandighede najaag wat hulle 'n hoër vlak van stimulasie bied ten einde optimale vlakke van kortikale opwinding te handhaaf. Navorsing toon dat ekstroverte gewoonlik in 'n toestand van laer kortikale opwinding verkeer vergeleke met introverte. Weens hulle geneigdheid tot hoër sintuiglike drempels en dus kleiner reaksies op sintuiglike stimulasie, het hulle méér daarvan nodig. Daarbenewens blyk *Nougesetheid ("Conscientiousness")* 'n positiewe invloed te hê op *Vertraagde Beloning ("Delay of Gratification")*. Gevolglik kan daar afgelei word dat eiewillige, versigtige en georganiseerde individue met 'n sterker neiging om selfdissipline te handhaaf meer waarskynlik 'n natuurlike superieure vermoë sal hê om onmiddellike beloning te verbeur in die strewe na 'n groter of meer waardevolle beloning op 'n latere tydstip. Boonop het die resultate aan die lig gebring dat *Ekstroversie* en *Neurotisisme ("Neuroticism")* 'n beduidende invloed op *Emosionele Selfbestuur ("Emotional Self-Management")* uitoefen. Dus is die gevolgtrekking dat *Ekstroversie* waarskynlik gepaardgaan met emosionele aanpassingstrategieë, waar individue met hierdie eienskap die vermoë toon om positiewe emosies te koester of te geniet (d.w.s. *Emosionele Selfbestuur*). Daarteenoor het die resultate daarop gedui dat individue met hoër vlakke van *Neurotisisme* meer gereeld emosionele wanaanpassingstrategieë gebruik en dus swakker vaar met die herstel van negatiewe emosies, wat tot 'n laer aanmelding van *Emosionele Selfbestuur* aanleiding gee. Volgens die resultate van die gemodereerde regressie was *Geslag* 'n beduidende moderator in die verwantskap *Neurotisisme – Risikotoleransie* en *Emosionele Selfbestuur – Risikotoleransie* onderskeidelik. Tweedens het empiriese steun vir *Inkomste* en *Opvoeding* as modereringsveranderlikes na vore gekom. Dit het getoon dat *Inkomste* en *Opvoeding* onderskeidelik die uitwerking van *Emosionele Selfbestuur* op *Risikotoleransie* beduidend modereer het.

Die navorsingsresultate bied insig in die tersaaklike faktore wat gebruik kan word om *Klient-/Beleggersrisikotoleransie* te bepaal. 'n Praktiese implikasie van die resultate is dat hierdie inligting gebruik kan word om beleggers in vier verskillende kliëntekategorieë of -profiele in te deel wat duidelik aan die hand van persoonlike eienskappe onderskei kan word. Elke profiel het eiesoortige behoeftes, wat bepaalde optrede van die finansiële raadgewer vereis.

'n Suksesvolle finansiële raadgewer is daartoe in staat om die tegniese kennis wat hy/sy deur omvattende finansiële onderrig opgedoen het toe te pas in 'n afrigtings- of raadgewingsbenadering wat die belegger in staat stel om 'n beleggingsbesluit te neem wat 'n balans handhaaf tussen maksimale gewin (finansieel) en maksimale sekerheid (emosioneel). Beleggers behoort aangemoedig te word om die maksimum hoeveelheid risiko te aanvaar op grond van hulle unieke kombinasie van objektiewe en subjektiewe eienskappe. Hoe die raadgewer te werk gaan om dít te bereik, vereis 'n begrip van individuele verskille en ander sosiodemografiese veranderlikes, en die vermoë om dit te gebruik om die kliënt in die korrekte kliëntekategorie te plaas en die gepaardgaande ondersteuning te bied.

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1.1 Introduction

"The economist may attempt to ignore psychology, but it is sheer impossibility for him to ignore human nature… If the economist borrows his conception of man from the psychologist, his constructive work may have some chance of remaining purely economic in character. But if he does not, he will not thereby avoid psychology. Rather, he will force himself to make his own, and it will be bad psychology."

(Clark, 1918, p. 4)

1.1.1 The need for a Client/Investor Risk-Tolerance structural model

Organisations are man-made phenomena that exist as a means through which society achieves its goals. In order to serve society for this purpose, the organisation is tasked with combining scarce factors of production into products or services with maximum economic utility. Hence, organisations have a major responsibility towards its stakeholders to efficiently combine and transform the lowest possible inputs into the highest possible outputs to ensure that economic value to the benefit of the stakeholders is created (Theron, 2013).

The Industrial/Organisational (I/O) Psychology and/or Human Resource (HR) function validates its inclusion in the spectrum of organisational functions through its commitment to contribute towards the organisation's goals and ultimately, its bottom line. The ideal is to develop and implement a range of integrated and coherent interventions that affect employee performance in such a manner that the monetary value of the improvement in performance exceeds the monetary value associated with the investment required to affect such an improvement (Burger, 2011; Swart, 2011; Theron, 2013).

The behaviour of man is not random, but rather a systematic expression of a complex nomological network of latent variables characterising the individual and his/her environment (Theron, 2013). In order for the I/O Psychology and/or HR function to professionally regulate a competent workforce, i.e. financial advisors, the principles that govern the behaviour of the financial advisor's client and consequently contribute to the advisor's performance (by enabling him/her to provide tailored services), must be identified and understood through empirical research. Research, in the field of I/O Psychology, is conducted in order to formulate close approximations of the truth or credible psychological explanations of the behaviour of man, i.e. the client, in order to demonstratively affect efficient, equitable performance improvement on the part of the financial advisor (Theron, 2013). Credible and valid theoretical explanations for the different facets of the behaviour of man represent a fundamental and indispensable, though not sufficient, prerequisite for efficient and equitable Human Resource Management (De Goede & Theron, 2010; Theron 2013).

The financial services sector is the largest sector in the world (Sutton & Jenkins, 2007), encompassing a comprehensive range of businesses including, among others, commercial banks, savings and loan associations, credit card companies, stock brokerages, and insurance companies. Inevitably, efficient financial services are fundamental to society in terms of economic growth and development (Herring & Santomero, 1995; Sutton & Jenkins, 2007). The importance of a well-functioning financial system was illustrated in the 2008 global financial crisis, which caused widespread social and economic devastation, including, amongst others, rising unemployment rates, poverty and increasing government debt (Verick & Islam, 2010).

In addition to providing payment services, an efficient financial system offers products that guard both firms and households against economic uncertainties by hedging, pooling, sharing, and pricing risks (Herring & Santomero, 1995; Sutton & Jenkins, 2007). An efficient financial sector reduces production costs and risks, as well as the costs and risks associated with trading goods and services, and consequently contribute significantly to increase standards of living (Herring & Santomero, 1995).

An efficient financial system facilitates the optimal allocation of resources to its most productive uses (Herring & Santomero, 1995). It expands the consumption possibility of individuals and increases accessibility to funds. Moreover, an extensive range of financial instruments allows individual investors to achieve their preferred trade-off between risk and return (Brandl, 1998; Herring & Santomero, 1995). However, to achieve this trade-off, individuals should have confidence in financial systems, and to foster this confidence requires sufficient flexibility by financial service providers and their employees to adapt to market needs, opportunities and conditions. Further to this Springford (2011) argues that consumer trust, i.e. "the reliance on an agent to act in your interest" (p. 20), is central to a competitive and well-functioning financial system. Consumer trust encourages investors to allocate their savings through financial markets and institutions as opposed to investing in non-productive assets (Herring & Santomero, 1995). Low levels of consumer trust lead to limited participation in financial markets, causing them to operate below potential (Springford, 2011), which in turn triggers low economic growth. The effect of low consumer trust was illustrated during the 2008 financial crisis when many investors felt that they had become unsuspecting victims of financial abuse (Ciro, 2012).

At the heart of the financial services sector lie competent financial advisors, who are responsible for providing valuable insight into the factors that affect the marketplace and economy. Competent financial advisors further possess knowledge and experience that enables them to combine a range of personal factors to determine *Client/Investor Risk-Tolerance*[1]. *Client/Investor Risk-Tolerance* serves as valuable input for the development of individualised financial or investment strategies that best meets the needs of the client, to ultimately reach his/her financial goals. *Client Risk-Tolerance* is the amount of uncertainty or investment return volatility (Hallahan, Faff, & McKenzie, 2003) that an investor is willing and able to accept (Grable, 1997; Grable, 2000; Grable, Archuleta, & Evans, 2009; Hallahan et al., 2003; Harlow & Brown, 1990; Roszkowski, Delaney, & Cordell, 2009) when making a financial decision. According to Callan and Johnson (2002) *Risk-Tolerance* is a complex psychological construct that encompasses an individual's values, beliefs, personal goals, and desire to feel confident and in control. Interventions focusing on enhancing the ability of the financial advisor to deliver sound financial advice will therefore be successful in as far as the financial advisor is able to grasp the comprehensive range of personal factors related to the individual client. Knowing how these factors combine to determine *Client Risk-Tolerance* will contribute to the efficient management of the behaviour of the financial advisor.

[1] *Client Risk-Tolerance*, *Investor Risk-Tolerance* and *Risk-Tolerance* is used interchangeably in this research study.

"At present the global marketplace is characterised by diversity among consumers… and of course the very unpredictable human psychological behaviour" (Shirazi, 2011, para. 4). It is in this milieu that the study of the client's inherent psychological wiring facilitates the creation of a conceptual and technical framework that may enable the financial advisor to attend to the more specific needs of the individual client. In an increasingly competitive marketplace, an in-depth understanding of individual client attitudes toward risk becomes central to financial advisors and institutions that wish to emphasise customer relations and retention (Fünfgeld & Wang, 2009). It is argued that through including a measure that has the ability to better predict *Client Risk-Tolerance* as part of their service provision, financial advisors can increase the effectiveness of their service provision. Moreover, the use of psychometrically sound instruments[2], that are multidimensional in content, may lend further credibility to the provision of their services. It should be acknowledged at the onset of this study that the implicit assumption is not that the financial advisor in his/her current capacity delivers a poor or unreliable service. All financial advisors are regulated under the Financial Intermediary and Advisory Services (FAIS) Act, which functions as a professional code of conduct guiding the service provision of the advisor (Viviers, personal communication, 19 March 2015). Under this code of conduct the advisor is compelled to use a risk-profiling method as an initial step in the investment or planning process. Therefore, many advisors already have such methods in place. The critical question is whether, and in what way, these methods can be improved on? It is in this respect that the current study aims to make a contribution.

Market segmentation in the financial industry is based, to a large extent, on demographic and socioeconomic characteristics as predictors of *Client Risk-Tolerance*. While these quantitative determinants of *Risk-Tolerance* do contribute to a better understanding of the client's *ability* to accept risk, it is argued in this study that an investigation into personality and emotion regulation variables could contribute improved insights into the *willingness* of these individuals to accept risk and thus, explain additional variance in *Client Risk-Tolerance.* A deeper knowledge of client decision-making under risky circumstances will enable the financial advisor

[2] The practical and legal limitations of the use of psychometric instruments by financial advisors are acknowledged and discussed in chapter 5.

to better predict patterns of investment or financial decisions. They will be able to clarify crucial questions as to how clients think, feel and reason, which will form the basis for the provision of adequate services and products. It is argued in this study that, based on variables independent of the more established and trusted demographic and socioeconomic variables, it will be possible to design a profile of different client types, which may assist financial advisors in identifying and analysing their clients. In this way, psychology becomes an important factor during the service provision efforts of the financial advisor. Therefore, this research will be geared towards establishing a diagnostic framework according to which individual clients can be analysed and classified into respective *Risk-Tolerance* categories.

It is argued in this research that the most prudent approach to delivering sound investment advice relies on the financial advisor's ability to assess and integrate two distinct sets of data pertaining to *Client Risk-Tolerance.* First, the advisor must evaluate a set of readily discernible demographic and socioeconomic variables unique to the client, so that an overall understanding of the client's *objective risk-tolerance* can be gained. Second, once the readily discernible objective factors have been assessed, the financial advisor should determine *Client Risk-Tolerance* to its full complexity, i.e. by including an assessment of a range of psychological variables, i.e. personality and emotion regulation variables. The latter is, what is referred to in this research study as *subjective risk judgment.*

It is therefore imperative to develop and empirically test a comprehensive explanatory *Client Risk-Tolerance* model, which identifies the most influential causal[3] factors underlying the two sets of predictors and the manner in which they interact within this model to ultimately affect *Client Risk-Tolerance*.

1.2 Background

In the past, researchers have attempted to broaden their understanding of individual investment management and decision-making through analysing the behaviour of

[3] The methodology applied in this study (i.e. structural equation modeling) is used for its explanatory nature. So although, strictly speaking, causality may not be inferred from the results, the structural model in itself does give a sense of how the nomological net of variables, possibly accounting for variance in *Risk-Tolerance*, may look.

investors[4] when faced with uncertain outcomes. Across the past several decades, studies on investment decision-making have concerned itself with the belief that economic agents, i.e. investors in the context of financial markets, apply rational calculations to economic and financial decisions (Kuzmina, 2010) and perform extensive analysis to establish the probabilities of success associated with specific rewards (Ricciardi, 2004). Economists traditionally assumed that when faced with uncertainty, individuals correctly form subjective probabilistic assessments according to the laws of probability (Rabin, 1998). This trend was perhaps due to the conventional finance notion of risk defined in terms of objective measures. Risk traditionally refers to "a situation in which a decision is made where the consequences depend on the outcomes of future events having known probabilities" (Lopes, 1987, p. 255). Therefore, it is based on mathematical rules, i.e. probabilities, and can be predicted statistically.

Theories such as the *Modern Portfolio Theory*[5] and the *Efficient Market Hypothesis*[6], focusing on paradigms such as portfolio allocations based on expected risk and return, the *Capital Asset Pricing Model*[7] and similar risk-based asset pricing models (Ricciardi & Simon, 2000; Subrahmanyam, 2007) have been awarded prominence in the field of finance and investment decision-making processes. Moreover, a number of behavioural propositions rooted within the behavioural finance paradigm have been studied, where attempts are made to understand the reasoning patterns of investors and the manner in which they utilise these reasoning patterns to create superior investment returns (Ricciardi & Simon, 2000). Such studies have

[4] Throughout this research, the terms "investors", "client" and "advisee" should be interpreted in a similar manner, all referring to the individual that seeks financial advice from a financial advisor.

[5] The *Modern Portfolio Theory* is a hypothesis introduced by Harry Markowitz that is based on the idea that it is possible to construct an efficient frontier of optimal portfolios that offers the maximum expected return for a defined level of risk. It supports the use of diversification as a means of reducing risks without changing or reducing expected return (Chen, Chung, Ho, & Hsu, 2010).

[6] The *Efficient Market Hypothesis* introduced by Eugene Fama is based on the assumption that "all stocks are perfectly priced according to their inherent investment properties, the knowledge of which all market participants possess equally" (Van Bergen, n.d., para. 1). According to this theory markets are efficient and current prices reflect all available information. Hence, attempts to outperform the market are essentially a game of chance as opposed to one of skill (Bisen & Pandey, 2015).

[7] The *Capital Asset Pricing Model* refined by William Sharpe gives an investor an appropriate expected rate of return for a project, given that the project's relevant risk characteristics are provided. The model holds that an investment's expected return "is lower when it offers better diversification benefits for an investor who holds the overall market portfolio" (Welch, 2014, p. 218), i.e. less required reward for less risk contribution. Projects contributing more risk require a higher expected rate of return for an investor to want them. In contrast to this projects contributing less risk require a lower expected rate of return for an investor to want them (Welch, 2014).

investigated *Expected Utility* and the *Prospect Theory*, but more recently academics and professionals have taken a renewed interest in individual preferences for, or attitudes toward risk.

The latest studies relating to financial decision-making have shown that people systematically depart from optimal judgment and decision-making (Filbeck, Hatfield, & Horvath, 2005; Kuzmina, 2010; Ricciardi & Simon, 2000). According to Engelberg and Sjöberg (2006) money behaviour, i.e. an individual's propensity to save or spend, is rarely rational and rather governed by influential and often unrecognised emotional forces. Other researchers such as Furnham (1996) and Lauriola and Levin (2001) have proposed that attitudes toward money and risk are a function of personality traits.

Central to the investigations regarding the factors that predict individual investment management decision-making has been the concept of risk. As mentioned, risk, according to Lopes (1987, p. 255), refers to "a situation in which a decision is made whose consequences depends on the outcomes of future events having known probabilities". Risk is a distinctive attribute for each individual due to the well-known fact that what one person perceives as a major risk, may be perceived by another person as a minor risk. Therefore, a vital aspect in understanding financial decision-making might be the subjective aspect of perceived risk versus the "objective risk" which is the sole foundation of conventional finance (Ricciardi, 2004). There exists a personal quality in determining the possibility of losses and gains. By recognising this, this research suggests that the traditional set of predictors of *Risk-Tolerance,* i.e. *objective risk-tolerance* (which typically includes variables such as *Age, Gender*, *Income* and *Education*) can be supplemented by focusing on predictors of *subjective risk judgment* (i.e. personality and emotion regulation), and in doing so the overall area of *Client Risk-Tolerance* (as measured by both sets of predictors, i.e. *objective risk-tolerance* and *subjective risk judgment*) can be improved on (Ricciardi, 2004).

For purposes of this research, the dependent variable *Client Risk-Tolerance* will be defined as the amount of uncertainty or investment return volatility (Hallahan et al., 2003) that an investor is *willing and able* to accept (Grable, 1997; Grable, 2000;

Grable et al., 2009; Hallahan et al., 2003; Harlow & Brown, 1990; Roszkowski et al., 2009) when making a financial decision. Individuals with higher levels of *Client Risk-Tolerance* generally have the ability to: (a) accept higher exposure to risk, (b) act with less information, and (c) require less control. In contrast to this, lower level individuals: (a) prefer lower chances of loss, (b) require more information regarding the performance of an investment, (c) tolerate less uncertainty, and (d) avoid unfamiliar situations (Grable, 1997).

According to Grable (1997) recent years have witnessed an upsurge of researchers and practitioners who have become increasingly concerned with understanding the concept of *Investor Risk-Tolerance* as input during the investment or portfolio allocation process. According to these scholars much of this renewed interest has "coincided with advances in the conceptualisation of investment management models" (Grable 1997, p. 1) that requires professionals to conduct a careful analysis of a client's *Risk-Tolerance* prior to proceeding with the investment process.

The CFA Institute (2010), for instance, proposes a "systematic approach to the investment process" through their curriculum (Bodie, Kane, & Marcus, 2008, p. 681). According to this approach, asset allocation is not an isolated choice, but rather forms part of a structured four-step investment process (CFA Institute, 2010). The first stage during this process requires the assembly of a policy statement, a highly customised document that is uniquely tailored to the preferences, attitudes and situation of each investor, which serves as a road map to guide the rest of this process (CFA Institute, 2010). Before the advisor can proceed to draw up such a statement, it is important that an exchange of information be facilitated between investor and advisor. The first step, therefore, requires gathering input regarding the objectives of the individual investor. The objectives, however, cannot be expressed only in terms of return on investment. This is due to the fact that most investors are aware that risk drives return and therefore, they will differ in their willingness to trade off expected return against risk (CFA Institute, 2010). This willingness is what is referred to as the *subjective risk judgment* component of *Risk-Tolerance* in this research. It can be argued that *Risk-Tolerance* is not only an important input in the investment process, but is a concept that should be adopted in a similar fashion by financial advisors across domains who are tasked with the duty of providing sound financial advice and assistance to clients about their personal financial matters[8].

Many efforts directed towards the understanding and predicting of *Client Risk-Tolerance* have focused on obtaining a mere summary of *Client Risk-Tolerance* (Bodie et al., 2008), where *Risk-Tolerance* is defined as a function of demographic and socioeconomic factors (Grable, 1997). Typically inputs such as life cycle stage and goals, time horizon, liquidity needs, tax concerns, and legal and regulatory factors are evaluated by the advisor, placing the prime focus on variables such as *Age, Gender, Marital Status, Education, Income* and *Occupational Status*. According to Filbeck et al. (2005), the key to successfully implementing an investment policy resides in the assessment of an individual's capacity for *and* attitude toward risk.

The tendency to analyse investors' *Risk-Tolerance* based on demographics and socioeconomic factors has produced the following predicting heuristics (Grable, 1997). These continue to be widely used to separate investors into high, average and low *Risk-Tolerance* categories (Grable, 1997):

(a) decreasing *Risk-Tolerance* is related to increasing *Age*;
(b) females are less risk-tolerant than males;
(c) unmarried individuals are more risk-tolerant than married individuals;
(d) individuals with a tertiary education are more risk-tolerant than those with a lower educational attainment;
(e) *Risk-Tolerance* increases with *Income*;
(f) individuals employed in professional, as opposed to non-professional occupations, tend to be more risk-tolerant;
(g) self-employed individuals are more risk-tolerant than those employed by others;
(h) *Risk-Tolerance* increases as asset holdings increase;
(i) higher levels of investor involvement in investment decisions are related to higher *Risk-Tolerance* levels;
(j) *Risk-Tolerance* increases with investment experience;

[8] For this reason, the terms investor and client will be used interchangeably.

(k) whites are more risk-tolerant than non-whites; and

(l) longer investment time horizons dictate higher *Risk-Tolerance* levels.

For purposes of this research this set of predictors will be referred to as *objective risk-tolerance* and will be defined in a manner that draws and extends on the traditional definitions of *Risk-Tolerance*. *Objective risk-tolerance* can ultimately be defined as the risk that an individual is capable of taking (Van de Venter, Michayluk, & Davey, 2012) against the backdrop of his/her demographic and/or socioeconomic status.

A plethora of financial management literature (Grable & Lytton, 1998; Roszkowski, Snelbecker, & Leimberg, 1993) and websites (such as Investopedia) support the aforementioned heuristics as mental short cuts to enable quick and efficient decision-making on behalf of the financial advisor. Whilst this might be helpful in some instances, it introduces room for error, especially in South Africa, where there are little studies devoted to empirically support (or reject) the use of these heuristics. Market segmentation plays an important role during the input stage of the investment process (i.e. setting of objectives), as it serves as a common method to better the understanding of, and service towards, a diverse customer base (Fünfgeld & Wang, 2009). It is valuable in recognising patterns of financial behaviour through studying segment predictors such as these that group individuals according to their needs. Whilst one cannot contest that these variables as inputs are indeed useful to the advisor, it provides a macro-level perspective, boxing clients into segments that fail to distinguish between the "risk-bearing properties of two otherwise unique clients in the same point of their planning horizon" (Harlow & Brown, 1990, p. 52). As Strydom, Christison, and Gokul (2009) rightfully points out, many of the relationships are based on stereotypical, often harmful, beliefs and judgments. Financial advisors are tasked with the responsibility of collecting reliable and relevant information from investors in order to avoid the possibility of misclassifying investors into the wrong *Risk-Tolerance* categories. Correctly understanding the predictors of *Risk-Tolerance* is an important issue for financial management if financial advisors are to optimise their service delivery.

Given the limitations of current *Risk-Tolerance* approaches as outlined above, it is proposed in this research that many other individual differences factors in isolation, as well as in a complex dynamic interaction with each other, could be identified that would influence individual *Risk-Tolerance.* This research aims to provide valuable insight into the factors that affect *Risk-Tolerance.* The aim is to provide a better understanding of how individuals in South Africa make financial decisions and to assist financial advisors to provide financial advice that is better tailored to suit the individual needs of investors. Toward this end, this research argues for the inclusion of *subjective risk judgment variables*, i.e. personality and emotion regulation, as an additional set of predictors when determining *Client Risk-Tolerance* levels. Once again it should be stressed that an assumption is not made that all advisors completely avoid personality and emotion based factors when determining *Client Risk-Tolerance*. In fact, there has been considerable headway in this regard. The assumption is rather that advisors may be using questionnaires that may be inadequately representative of the range of individual difference factors that combine to determine *Risk-Tolerance.*

It is, therefore, argued that the investigation of factors that determine financial *Risk-Tolerance* should be expanded beyond the testing of purely objective factors as predictors with limited diagnostic value. For example, Sokol-Hessner, Camerer, and Phelps (2012, p. 1) have argued that “financial decision-making is not dispassionate but instead fundamentally supported by emotions”. Furthermore, human beings, by virtue of their genetic predispositions, i.e. personality, will differ in their attitudes toward decision-making (Belcher, 2007). Therefore, it is proposed that research regarding the influence of personality and emotion regulation should be conducted to expand the existing literature on financial decision-making, with specific reference to *Client Risk-Tolerance*.

In this study the use of demographic and socioeconomic variables as sole predictors of *Risk-Tolerance* is contested. Instead, in this study the need is argued for a second set of predictors of client *Risk-Tolerance* that firstly, is multidimensional in content and secondly, is empirically based and statistically sound. For this to be effected, however, an elaboration in terms of a second set of predictors of *Risk-Tolerance* is proposed. This group of variables will be referred to as *subjective risk judgment* in which *Risk-Tolerance* is conceptualised as a function of personal preferences*.* For the purposes of this research, therefore, the following definition of *subjective risk judgment* was developed:

> "The level of risk that an individual[9] prefers to take and is willing to accept given aspects of his/her personality and ability to self-regulate his/her emotions".

The following sections will discuss literature related to *subjective risk judgment* variables that have been shown to be predictors of *Client Risk-Tolerance*. An overview of the various variables is provided. However, given the complexity of the proposed conceptual model[10] (figure 2.2), not all of the variables discussed here was included in the current empirical research. The aim with these discussions is to indicate how the variables relate to *Risk-Tolerance* within a complex nomological net of variables (i.e. depicted in the conceptual model, figure 2.2) that could be used to explain variance in *Risk-Tolerance.* For those variables that are included in the current empirical research, the relevant hypotheses are presented as part of the literature study.

According to Carducci and Wong (1998, pp. 355-356) the *Type A* personality is characterised by "individuals who are hard driving and competitive, with an underlying tendency for hostility and aggressiveness, and a heightened sense of time urgency and impatience". This behaviour pattern has been theorised to translate into a willingness to take greater personal risk to maximise achievement in intellectual and physical pursuits.

Sensation Seeking is a personality factor that has consistently been found to correlate with *Risk-Tolerance* (Blaszczynski, Wilson, & McConaghy, 1986; Corter &

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[9] The focus of this research is on the individual investor and thus, the definition does not include reference to institutional investors who invest on behalf of individuals and who are regulated by mandates that dictate how they should invest.

[10] The initial aim of the study was to capture the hypothesised effects in a structural model and to test the fit of the structural model to a data set via structural equation modeling (SEM). However, it became apparent that it would not be possible to test the hypothesised interaction effects in this manner and thus, the interaction effects could not be included in the structural model. For this reason it was decided to construct a reduced structural model without the hypothesised interaction effects as well as an overarching conceptual model that captures the full range of hypotheses. SEM was used to test the reduced structural model. The interaction effects were tested with a series of moderated regression analyses.

Chen, 2006; Wong & Carducci, 1991; Young, Gudjonsson, Carter, Terry, & Morris, 2012). Zuckerman defined *Sensation Seeking* as a biologically based personality dimension. He proceeded to define sensation seekers as individuals "who seek varied, novel or complex sensations or experiences" (Blaszczynski et al., 1986, p. 113) and display a "willingness to take physical and social risks for the sake of such experiences" (Corter & Chen, 2006, p. 370; Wong & Carducci, 1991, p. 525).

Anxious individuals display an attentional bias towards threatening information. Trait anxiety, as a personality characteristic, is typically defined as "an enduring tendency to react to many situations with anxiety and fear" or "a vulnerability to respond anxiously to stress and psychological threat" (Reiss, 1997, pp. 202-204). In tandem with subjective feelings of doubt and insecurity (Fünfgeld & Wang, 2009), the propensity to experience anxiety may lead to the overestimation and consequent avoidance of risk (Lauriola & Levin, 2001).

Optimism as a personality trait is typically defined as individuals' tendency to rate themselves as being less at risk than their peers and to expect a lower probability of negative outcomes. Optimistic individuals display a higher propensity to undertake risk (Belcher, 2007).

Locus of Control explains whether an individual views rewards as contingent upon his/her own behaviour, i.e. *Internal Locus of Control*, or as under the control of powerful others, as unpredictable, by luck, chance or fate, i.e. *External Locus of Control* (McInish, 1982). Belcher (2007) argued that the willingness to bet on uncertainty is a function of *competence*, which can be defined as what an individual knows relative to what can be known in a given situation. Subsequent success or failure of events is conditioned by a feeling of competence, because an individual's assessment of and sense of control in a given situation will depend on this feeling of competence. Thus, it has been argued that a greater sense of personal control (i.e. knowledge, familiarity and experience in a particular situation), or *Internal Locus of Control*, will activate a greater sense of risk-taking (Belcher, 2007).

Impulsivity tends to cloud judgment (Belcher, 2007) and generates careless decision-making (Lauriola & Levin, 2001). Individuals high on *Impulsivity* that engage in risk-taking behaviour will often do so without thorough assessment of the consequences (Belcher, 2007). In contrast to this, individuals ranking low on *Impulsivity* are more likely to perform over-careful analysis of their choices, which creates a conflict of values and unpleasant emotions in addition to this. Therefore, the riskless options are preferred in an attempt to reduce such emotions (Lauriola & Levin, 2001).

The *Big 5 Personality Model* is the most comprehensive and accepted measurement of personality (Mayfield, Perdue, & Wooten, 2008) and has been confirmed by research as important in understanding risk behaviour (Nicholson, Soane, Fenton-O'Creevy, & Willman, 2005). Moreover, personality as defined by the Big Five taxonomy has been shown to be a causal factor of *Risk-Tolerance* (Nicholson, Fenton-O'Creevy, Soane, & Willman, 2002).

A few empirical studies support the relevance of the Big Five or five factor model in predicting *Client Risk-Tolerance*. Nicholson et al. (2005) found that *Extraversion* and *Openness to Experience* were positively associated with risk-taking (as measured by the Risk Taking Index – a measure of risk-taking in the domains of health, career, recreation, finance, safety and social risk). Further to this, it was found that *Neuroticism*, *Agreeableness* and *Conscientiousness* were inversely associated with risk-taking (Nicholson et al., 2005).

The inability to *Delay Gratification* is associated with the tendency of individuals to sacrifice long-term goals in favour of short-term goals, allowing them to experience an immediate gratification (Tice & Bratslavsky, 2000). Individuals with an unwillingess to postpone gratification display risky behaviour and self-regulatory deficits in various spheres of life (Wulfert, Block, Santa Ana, Rodriguez, & Colsman, 2002).

In addition to studies in the domain of the effects of personality characteristics on risk judgment, emotions and emotional behaviours, within in broader framework of emotion regulation, have also recently been studied within this context. Emotions are triggered by a particular situation and play an adaptive role in speeding up the decision-making process by narrowing down the individual's options for actions –

either discarding dangerous actions or endorsing advantageous actions (Shiv, Loewenstein, Bechara, Damasio, & Damasio, 2005). Individuals differ in the strength and speed of their positive and negative reactions depending on what aspect of a stimulus stands out as the most salient at any particular time. In decisions about risky activities, emotional reactions usually result in behavioural outcomes that diverge from what people consider as the optimum outcome of a decision (Ricciardi, 2004). Moreover, there are circumstances in which a naturally occurring emotional response must be inhibited or enhanced to ascertain a wiser decision. In this regard, emotion regulation has been shown to have a beneficial role in risky decision-making (Heilman, Crişan, Miclea, Miu, & Houser, 2010; Sokol-Hessner et al., 2012).

Emotion regulation is a specific form of self-regulation that involves overriding one set of emotion responses with another, incompatible set of emotional expressions or experiences (Tice & Bratslavsky, 2000). Emotion regulation refers to the processes by which control over the type and intensity of emotions that individuals experience and express is exerted (Gross, 1998). Moreover, emotion regulation falls within the broader framework of emotional intelligence, which is defined as the ability to purposely adapt, shape and select environments through the use of emotionally relevant processes (Gignac, 2010). Emotional intelligence refers to the individual ability to recognise and interpret emotions, and to use and integrate them productively to facilitate optimal reasoning and decision-making (Ameriks, Wranik, & Salovey, 2009). Within this framework there are two specific dimensions that constitute the underlying dimensions of emotion regulation, i.e. *Emotional Self-Management* and *Emotional Self-Control*.

Emotional Self-Management is a proactive emotion regulation strategy that measures the relative frequency with which individuals manage their own emotions successfully. It generally focuses on the ability to successfully adjust to negative emotional states with some focus on engaging in activities that maintain positive emotional states. *Emotional Self-Control* is a reactive strategy that measures the relative frequency with which individuals control their strong emotions appropriately. The focus is placed on noticeable maintenance of focus in the face of emotional adversity. This, in contrast to *Emotional Self-Management*, concerns a behavioural demonstration of controlling intense reactive emotions.

The use of *Emotional Self-Management* is considered effective in decreasing stimulation related to the anticipation of reward and loss aversion. More specifically, *Emotional Self-Management* enables riskier financial decision-making by effectively down regulating negative emotional experience in relation to stress and anxiety. The use of *Emotional Self-Control* allows for the control or suppression of strong positive or negative emotions associated with risky financial decision-making and can therefore decrease risk aversion. It endows the individual with the ability to stay focused (Gignac, 2010) and it is argued that *Emotional Self-Control* may instil a sense of rationality when making decisions that are initially emotionally laden.

Financial institutions have an obvious and vested interest in accurately predicting *Risk-Tolerance* levels of their clients. The ability to accurately gauge *Risk-Tolerance* levels is important in a few major respects, beyond the regulatory requirement, as outlined above. Balancing clients' need for financial growth and security with their actual appetite (or preference) for risk may serve to enhance their levels of trust in service delivery, increasing overall participation in financial markets and facilitating economic growth.

Risk-Tolerance levels most certainly vary from one investor to the next, where two individuals with identical demographic and socioeconomic characteristics may possess polar opposite risk personalities. However, efforts to measure these definitive characteristics of individuals require significantly more research. Many scholars and advisors continue to measure, or make tentative predictions based on demographic/socioeconomic factors. These predictions assume that investors who are alike in terms of these factors find comfort in adopting the same level of risk when making financial decisions. Others may use *Risk-Tolerance* questionnaires that relate somewhat to personality based factors, but that lack sufficient validation.

1.3 Research Aim and Objectives

In recent years there has been an increased awareness of the explanatory power than can be achieved by aligning economic and psychological research agendas. More specifically psychology is the science of human behaviour, i.e. it systematically explores human judgment, behaviour and decision-making (Rabin, 1998). Within this domain personality is described as a relatively stable and enduring force that influences cognition, decision-making and behaviour and naturally, it would include the study of financial behaviour. Emotion regulation is another psychological characteristic that describes how effectively an individual identifies, understands and with specific reference to the study objectives, regulates emotions and uses them when engaging in complex problem solving and decision-making (Ameriks et al., 2009). Thus, it is argued in this study that personality and emotion regulation has the ability to increase our understanding of how humans differ in the ways that they appraise risk when making financial decisions.

It is hoped that this research will add to the growing body of literature documenting the psychological correlates of financial decision-making under conditions of risk and uncertainty. More specifically, an attempt will be made to gain a more nuanced view of the complex nomological network of relationships that influence *Client Risk-Tolerance.* To the author's knowledge, there currently exists no research in South Africa that jointly considers psychological and demographic/socioeconomic variables as predictors of *Client Risk-Tolerance*.

The research initiating question asks why there is variance in *Risk-Tolerance* amongst clients in need of financial advice. Therefore, this research study aims to determine whether personality and emotion regulation variables (i.e. *subjective risk judgment*), as well as demographic and socioeconomic variables (i.e. *objective risk-tolerance*) of the individual can be used to differentiate amongst different levels of *Client Risk-Tolerance.* More specifically, the research study aims to determine the manner in which the various personality and emotion regulation latent variables are moderated by the demographic and socioeconomic latent variables to affect *Client Risk-Tolerance*. The findings will produce estimates of which of the various predictors are statistically significant in predicting *Client Risk-Tolerance*.

The research objectives include:

(a) develop a conceptual model[11] that depicts the complex dynamics of the

[11] The initial aim of the study was to capture all the hypothesised effects (direct and indirect effects, as well as moderator effects) in a structural model and to test the fit of the structural model to a data set via SEM. However, due to SEM restrictions in terms of the amount of observed variables to

psychological (*subjective risk judgment*), and demographic and socioeconomic (*objective risk-tolerance*) variables in predicting *Client Risk-Tolerance*;

(b) test the fit of the reduced structural model to a data set;

(c) investigate the modification indices of the reduced model as recommendations for adjustments to the model, and

(d) test the various hypothesised interaction effects (indicated in the conceptual model), with a series of moderated multiple regressions.

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operationlise latent variables, it was not possible to test the hypothesised interaction effects in this manner and thus, the interaction effects could not be included in the structural model. For this reason it was decided to construct a reduced structural model without the hypothesised interaction effects as well as an overarching conceptual model that captures the full range of hypotheses. SEM was used to test the reduced structural model. The interaction effects were tested with moderated regression analyses.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

In recent years, researchers and practitioners (in both psychology and financial management) have become increasingly concerned with understanding the concept of *Investor Risk-Tolerance* as input during the investment or portfolio allocation process. Much of this renewed interest has coincided with advances in the conceptualisation of investment management models (Grable & Lytton, 1999), such as the four-step investment process proposed by the CFA Institute (2010), that require professionals (i.e. financial advisors) to conduct a careful analysis of a client's *Risk-Tolerance* prior to proceeding with the investment process. *Risk-Tolerance* is a highly influential factor that has the ability to determine the appropriate composition of portfolios that are optimal in terms of the risk and return relative to the needs of the individual (Hallahan, Faff, & McKenzie, 2004). Similarly, it can be argued that knowledge regarding an individual's *Risk-Tolerance* is not only an important input in the investment process, specifically, but it is a concept that should be adopted in a similar fashion by financial advisors across domains, who are tasked with the duty of providing sound financial advice and assistance to clients about their personal and everyday financial matters. According to Roszkowski et al. (2009) the foundation of any financial plan is the *Risk-Tolerance* of the client and therefore, it requires extensive assessment.

Not only do financial advisors have a fiduciary duty to have extensive knowledge and understanding of their clients' circumstance and preferences (Van de Venter et al., 2012), but also, the marketplace is becoming increasingly competitive warranting the need to focus on client relationships and the retention of clients (Fünfgeld & Wang, 2009). It is argued that through increasing the knowledge base of how *objective risk-tolerance* and *subjective risk judgment* factors combine to predict overall *Risk-Tolerance,* financial advisors can utilise this information to increase the effectiveness of their services. Moreover, the measurement of *subjective risk judgment* variables necessitates the use of psychometrically sound instruments[12]. This study will aim to identify appropriate instruments by investigating the psychometric integrity thereof, in order to add to the body of knowledge regarding sound scientific predictors of *Risk-Tolerance*. In this way this study aims to illustrate that the assessment of *Client Risk-Tolerance* should be multidimensional by nature, which may lend further credibility to the provision of services by financial advisors.

It is argued that the most prudent approach to delivering sound investment advice would rely on the financial advisor's ability to assess and integrate two distinct sets of data pertaining to overall *Client Risk-Tolerance,* that is, the combination of the client's *objective risk-tolerance* as well as his/her *subjective risk judgment* assessment. Firstly, the advisor must evaluate a set of demographic and socioeconomic variables unique to the client so that an overall understanding of the client's *objective risk-tolerance* can be gained. Secondly, once the readily discernible objective factors have been assessed, the financial advisor should proceed to determine *Client Risk-Tolerance* to its full complexity, by including an assessment of a range of personality and emotion regulation variables. The latter is what is referred to in this research study as *subjective risk judgment.*

This line of reasoning culminates into the potential classification of clients into four different client categories or profiles (figure 2.1) that are clearly distinguishable in terms of their personal characteristics. Each profile raises unique needs warranting different actions on the part of the financial advisor (table 2.1). The figure combines four quadrants representing four types of investors based on their unique combined levels of *objective risk-tolerance* (ORT) and *subjective risk judgment* (SRJ). Firstly, high ORT-high SRJ individuals (quadrant 1) possess sufficient financial resources to spend/invest and time to recover losses, as determined by demographic and socioeconomic characteristics. This is accompanied by a personal preference or willingness to assume high-risk decisions. Secondly, low ORT-high SRJ individuals (quadrant 2) have limited financial resources to spend/invest and little time to recover losses, but a personal preference or willingness to assume higher risk decisions. Thirdly, the high ORT-low SRJ individual (quadrant 3) has sufficient financial

[12] The legal limitations attached to the use of such instruments by financial advisors are discussed in chapter 5.

resources to spend/invest coupled with increased time to recover losses, but a personal preference or willingness to assume lower risk decisions. Lastly, low ORT-low SRJ individuals (quadrant 4) have limited financial resources to spend/invest and little time to recover any losses, as determined by demographic and socioeconomic characteristics. This is accompanied by a personal preference or willingness to assume lower risk decisions, as a result of certain personality and emotion regulation variables. It is argued that quadrants 2 and 4 will require a more conservative approach on the part of the financial advisor when delivering investment advice. Quadrants 1 and 3 require the financial advisor to employ a strategy that promotes confident investment or financial decision-making on the part of the investor.

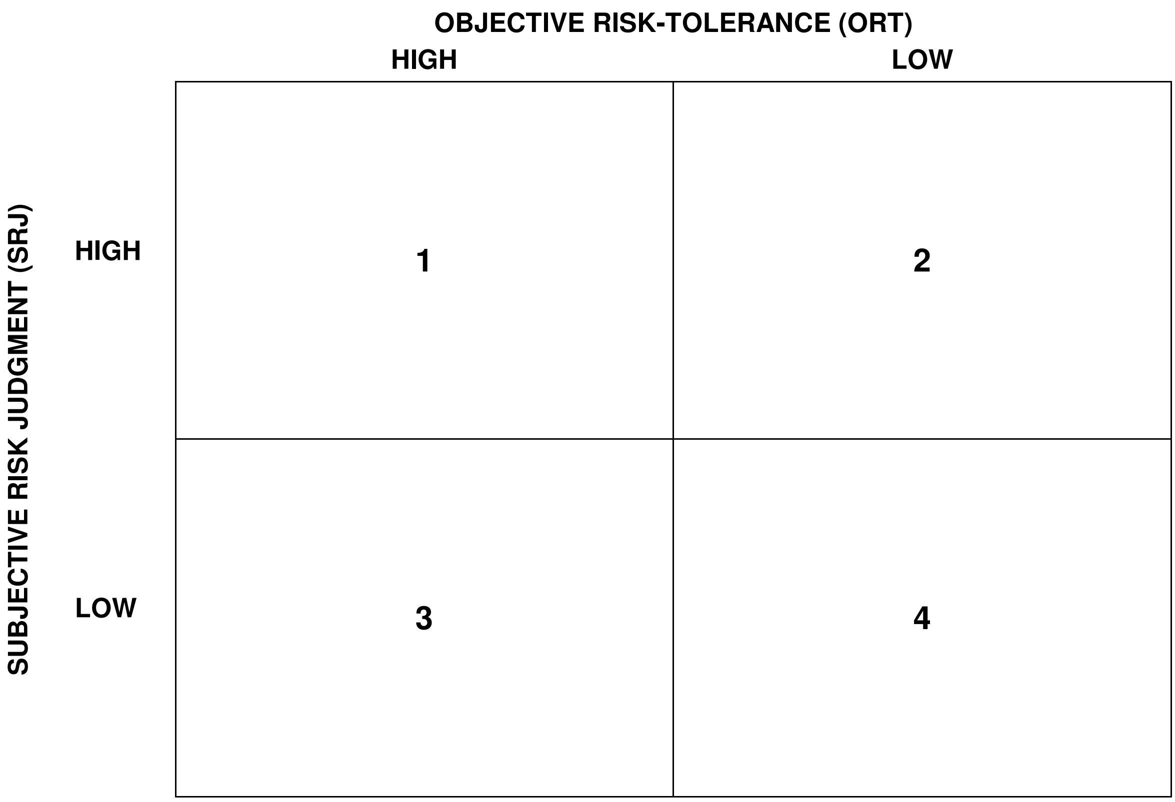

Figure 2.1. **Client risk profiles**

Table 2.1

Client profile description and action plan

PROFILE	DESCRIPTION	ACTION
HIGH ORT – HIGH SRJ	The investor has sufficient financial resources to spend/invest and time to recover losses, as determined by demographic and socioeconomic characteristics. This is accompanied by a personal preference or willingness to assume high-risk decisions.	The financial advisor will assist such an individual to make high risk-high return investments.
LOW ORT – HIGH SRJ	The investor has limited financial resources to spend/invest and little time to recover losses, but a personal preference or willingness to assume higher risk decisions.	The financial advisor will assist the individual to make more conservative investment choices.
HIGH ORT – LOW SRJ	The investor has sufficient financial resources to spend/invest and time to recover losses, but a personal preference or willingness to assume lower risk decisions.	The financial advisor will assist such an individual to make moderate risk investments and educate the individual in making more confident investment choices.
LOW ORT – LOW SRJ	The investor has limited financial resources to spend/invest and little time to recover any losses, as determined by demographic and socioeconomic characteristics. This is accompanied by a personal preference or willingness to assume lower risk decisions.	The financial advisor will provide the individual with a broad spectrum of financial education and advice services. All together risky investments should be avoided.

Despite the renewed interest in the concept of *Client Risk-Tolerance* and its importance as an essential ingredient in investment portfolio construction and personal finance decisions, the role of *subjective risk judgment* factors (e.g. the Big Five personality factors, i.e. *Openness to Experience, Conscientiousness, Extraversion, Agreeableness,* and *Neuroticism,* as well as emotion regulation) has not received much research attention (Grable & Lytton, 1998). The primary reason for this paucity appears to be a general lack of understanding of the determinants of *subjective risk judgment* (Harlow & Brown, 1990) and how these subjective factors contribute to the prediction of *Client Risk-Tolerance* over and above, and in combination with, the contribution made by the *objective risk-tolerance* factors. Therefore, a formal definition of *subjective risk judgment* is necessitated to clarify its role in determining *Client Risk-Tolerance*. It should, however, be acknowledged that that the Behavioural Finance paradigm is still young and evolving. Therefore research geared towards improving the understanding of the psychological factors that affect decision-making under risk and uncertainty is limited (Subash, 2012). Consequently, the inclusion of information in formal educational programmes that are geared towards improving this understanding amongst advisors are also limited. Therefore, it would not be reasonable to expect of advisors and academics alike to have extensively engaged in related research endeavours and consequently, possess such insights.

In the subsequent sections of the literature study an attempt will be made to produce a systematic and reasoned argument in support of a conceptual model that explicates the manner in which personality and emotion regulation variables influence *Client Risk-Tolerance*, in isolation, as well as in a complex dynamic interaction with each other, to determine more comprehensive client risk profiles. Moreover, the conceptual model will explicate the manner in which these personality and emotion regulation variables are moderated by demographic and socio-economic variables to predict overall *Client Risk-Tolerance.* Firstly, a definition of the dependent variable, *Client Risk-Tolerance*, will be provided. Secondly, a definition of *objective risk-tolerance* is constructed, followed by an overview of literature devoted to the *objective risk-tolerance* variables, i.e. demographic and socioeconomic variables, as one set of predictors of *Risk-Tolerance*. Thirdly, a definition of *subjective risk judgment* is constructed, followed by an overview of *subjective risk judgment variables*, i.e. personality and emotion regulation variables, as an additional set of predictors of *Client Risk-Tolerance*. Lastly, this section will introduce the proposed *Client Risk-Tolerance* conceptual model. The identity of each proposed construct comprising *objective risk-tolerance* and *subjective risk judgment* will be established and individually defined and discussed, in terms of the relevant literature, in order to systematically uncover the logic underlying the model's structure.

2.2 Defining the Dependent Variable: Client Risk-Tolerance

In everyday language *Risk-Tolerance* refers to the "willingness to take a chance". Formal textbook definitions devoted to investment management treat *Risk-Tolerance* as an individual's ability to endure market volatility (Roszkowski et al., 2009), or the level of risk an individual is willing to accept when making an investment (Du Toit, Erasmus, Kotze, Ngwenya, Thomas, & Viviers, 2010). However, since the

development of *Risk-Tolerance* assessment methodologies, there have been numerous attempts at constructing definitions that carry greater intuitive appeal.
In as early as 1978, Schaefer defined *Risk-Tolerance* as the maximum amount of investment risk that someone is comfortable taking (as cited in Grable, 1997). MacCrimmon and Wehrung (1986) explained that one would expect an individual with a high level of *Risk-Tolerance* to accept a higher exposure to risk in the sense of taking sole responsibility, acting with less information and requiring less control when compared to an individual who has a lower *Risk-Tolerance*.

According to Harlow and Brown (1990, p. 51) *Risk-Tolerance* refers to the “degree to which an investor is willing and able to accept the possibility of an uncertain outcome to an economic decision”. They suggest a measure of *Risk-Tolerance* to be useful in summarising an investor’s perception about the trade-off between risk and the compensation required for bearing risk. In 1997, Grable suggested that high *Risk-Tolerance* individuals accept volatile events in comparison to low *Risk-Tolerance* individuals who require certainty. A similar definition to that of Harlow and Brown (1990) is given by Grable (2000), which describes *Risk-Tolerance* as the degree to which an investor is willing to accept the possibility of an uncertain outcome when making a financial decision.

Hallahan et al. (2003, p. 484) provided an account of the term being widely used to refer to an investor’s attitude toward risk and states that *Risk-Tolerance* is “the amount of uncertainty or investment return volatility that an investor is willing to accept when making financial decisions” and “the extent to which an individual is prepared to risk experiencing a less attractive outcome in pursuit of a more attractive outcome”. Similarly, Roszkowski et al. (2009) referred to it as the extent to which an individual is willing to accept the possibility of experiencing a less favourable outcome in search of a more favourable outcome. Grable (2000) provided a comprehensive definition of *Risk-Tolerance* as the degree to which an individual is willing to pursue an uncertain course of action, offering a relatively large reward, as opposed to a more certain course of action in which the reward is comparatively smaller. *Risk-Tolerance* is generally considered as the inverse of the economist’s concept of risk aversion (Strydom & Metherell, 2012).

For purposes of this research, a combination of the traditional definitions of *Risk-Tolerance* will be utilised to ultimately define the dependent variable, *Client Risk-Tolerance*. *Client Risk-Tolerance* is, therefore, defined as the amount of uncertainty or investment return volatility (Hallahan et al., 2003) that an investor is willing and able to accept (Grable, 1997; Grable, 2000; Grable et al., 2009; Hallahan et al., 2003; Harlow & Brown, 1990; Roszkowski et al., 2009) when making a financial decision.

Individuals with higher levels of *Client Risk-Tolerance* generally have the ability to: (a) tolerate larger losses, (b) accept higher exposure to risk (knowing that there might be larger gains in the future), (c) act with less information, and (d) require less control. In contrast to this, lower level individuals: (a) prefer lower chances of loss and thus, (b) take comfort in lower-risk investments (knowing that there is a lower but more certain return), (c) require more information regarding the performance of an investment, and (d) tolerate less uncertainty.

2.3 Defining the Predictors

2.3.1 Objective risk-tolerance

The assessment of *Client Risk-Tolerance* has commonly revolved around a single method using a single set of predictors, that is, financial services professionals commonly use heuristic judgments that are based on demographic and socioeconomic characteristics, to assess and predict *Client Risk-Tolerance*. This method assumes that there exists a strong correlation between demographic and socioeconomic characteristics and *Risk-Tolerance*. For purposes of this research, this set of predictors will be referred to as *objective risk-tolerance* and can ultimately be defined as the risk that an individual is capable of taking (Van de Venter et al., 2012) against the backdrop of his/her demographic and/or socioeconomic status.

A significant amount of evidence and agreement has been found in support of a statistical relationship between *Risk-Tolerance* and a number of these factors, including *Age*, *Gender*, *Marital Status*, *Family Size*, *Education*, *Income/Wealth*, *Occupational Status*, and *Race/Ethnic Origin*. A few additional factors, for example, *Time Horizon* and *Investment Experience*, have also been subjected to investigation. The following section aims to provide a concise overview of previous research findings that support the use of the variables listed above as a means of differentiating among levels of investor *Risk-Tolerance*. In sections 2.5 and 2.6 the most theoretically and statistically salient variables pertaining to *Risk-Tolerance* will be discussed in order to warrant their inclusion within the proposed *Client Risk-Tolerance* conceptual model. More specifically, the interest of this research will be vested in exploring those demographic and socioeconomic variables that have yielded inconsistent findings in previous studies.

The following characteristics have emerged (mainly from studies conducted in the United States) as significant determinants of *Client Risk-Tolerance.* It has subsequently become common practice to use them as predicting heuristics when determining *Client Risk-Tolerance*.

2.3.1.1 Age

Over the past few decades, research focusing on the relationship between *Age* and *Risk-Tolerance* has largely accepted the life-cycle hypothesis, i.e. that an inverse or negative causal relationship exists between *Age* and *Client Risk-Tolerance*. This is based on the popular notions that individuals become more cautious as they mature and that younger investors tend to have a longer expected number of years to recoup their losses or to enjoy their gains (Strydom & Metherell, 2012). Numerous studies have replicated findings to support this line of reasoning (Baker & Haslem, 1974; Hallahan et al., 2004; Hawley & Fujii, 1994; Lewellen, Lease, & Schlarbaum, 1974; McInish, 1982; Strydom & Metherell, 2012).

2.3.1.2 Gender

The assumption that men generally should, and do, take more financial risks than women continues to have credence within the investment/financial management community. An early study by Lytton and Grable (1998) revealed that males generally expressed more confidence in their financial situations and have higher risk-taking propensities in relation to financial management strategies, than women. Subsequent research on the topic has largely supported this belief that men favoured and held more risky assets compared to women, who supposedly choose to invest financial resources more conservatively due to lower *Risk-Tolerance* levels

(Croy, Gerrans, & Speelman, 2010; Hallahan et al., 2004; Strydom & Metherell, 2012).

2.3.1.3 Marital status

Financial advisors support the notion that *Marital Status* (i.e. married, never married, divorced, separated, and widowed) is a significant predictor of clients' risk and return preferences. In a longitudinal study of *Risk-Tolerance* Van de Venter et al. (2012) theorised that single individuals, having fewer responsibilities and less to lose when accepting greater financial risks, will tend to display a greater propensity towards being risk-tolerant. In contrast to this, married individuals become less risk-tolerant due to a greater need for protection of wealth for future utilisation (i.e. children, housing and retirement). Studies conducted by Baker and Haslem (1974); Cohn, Lewellen, Lease, and Schlarbaum (1975); Hawley and Fujii (1994); Roszkowski, Snelbecker, and Leimberg (as cited in Grable, 1997); and Yao, Hanna, and Lindamood (2004) support the notion that being married has a significant negative relationship with *Risk-Tolerance*.

2.3.1.4 Family size

Lewellen et al. (1974) found some support for the notion that investors with an increasing amount of dependents adopt a more conservative investment stance. Grable and Joo (1999) provided further support for this, reporting that the number of dependents was statistically negatively significant, indicating that the more dependents an individual has, the less risk-tolerant he/she becomes. It can be argued that an increasing number of dependents will result in an increasing concern for financial security. Therefore, and individual may be more likely to focus on sustaining a secure financial position to ensure that he/she is able to provide for his/her dependents in the present, as opposed to incurring risk for an uncertain, possibly higher, future reward.

2.3.1.5 Education

Educational attainment of an individual is another factor that has been proposed as a significant predictor of *Risk-Tolerance*. It is argued that higher *Education* levels may increase an individual investor's ability to evaluate risks inherent to the investment process and therefore, endow them with a higher financial *Risk-Tolerance* (Hallahan et al., 2003). Scholars such as Hallahan et al. (2004) and Van de Venter et al. (2012) reported that a trade or tertiary diploma level of education was necessary for a significant increase in *Risk-Tolerance* to be perceived.

2.3.1.6 Income

According to Grable (1997) increased levels of *Income* has become a commonly accepted characteristic of high risk-tolerant individuals. Financial advisors have determined that increasing *Income* levels are associated with superior access to immediate resources, leading to the assumption that higher levels of *Income* lead to higher levels of *Risk-Tolerance*. Support for the positive relationship between *Income* and *Risk-Tolerance* has been generated by numerous studies (e.g. Baker & Haslem, 1974; Cohn et al., 1975; Croy et al., 2010; Hawley & Fujii, 1994; Yao et al., 2004).

2.3.1.7 Occupational status

According to Grable (1997) certain occupations and employment classifications presumably appeal to individuals with higher *Risk-Tolerance* levels. More specifically, it has been found that nonprofessional occupations (e.g. clerical workers and un/skilled labourers) tend to display lower *Risk-Tolerance* levels, whereas professional occupations (e.g. educators, doctors, lawyers, business owners, and managers) display superior *Risk-Tolerance* levels. This line of reasoning is based on arguments by Barnewall (1988) that nonprofessional occupations carry smaller economic and political risks. In addition, Yao et al. (2004) concluded that there existed a significant positive relationship between *Risk-Tolerance* and self-employment. Hallahan et al. (2004) revealed that retired individuals (60+) display lower levels of *Risk-Tolerance*.

2.3.1.8 Ethnic group origin

Research regarding the relationship between financial *Risk-Tolerance* and *Race/Ethnicity* mainly orginates from the United States with a few studies suggesting that White individuals are more risk-tolerant than their non-White counterparts (Grable, 1997; Haliassos & Bertaut, 1995; Hawley & Fujii, 1994). A more recent study by Yao, Gutter, and Hanna (2005) suggested that cultural experience, values and the socialisation of minorities were predictors of *Risk-Tolerance* levels. The historical lack of exposure to financial markets and financial information, as well as factors such as unstable labour force participation, discrimination and lower levels of wealth lead to lower levels of *Risk-Tolerance*. Hence, the conclusion that Blacks and Hispanics possess lower *Risk-Tolerance* levels when compare to Whites.

In South Africa, few empirical studies exist that have investigated the relationship between *Race* and *Investor Risk-Tolerance.* A study by Strydom et al. (2009) and Gumede (2009) revealed contradictory results. The prior suggested that Whites were significantly less risk-tolerant than both Blacks and Indians[13] in their study. In contrast, Gumede (2009) revealed that Whites were more risk-tolerant than Blacks, Asians/Indians and Coloureds. Moreover, a more recent study by Strydom and Metherell (2012) found the relationship between *Race* and *Risk-Tolerance* to be insignificant.

2.3.1.9 Investment experience

In a study by Corter and Chen (2006) *Investment Experience* proved to be a significant predictor of *Risk-Tolerance*, where more experience equaled increased *Risk-Tolerance*, as well as more risky investment portfolios. This is due to the assumption that an individual's investment knowledge increases as his/her *Investment Experience* increases.

2.3.1.10 Time horizon

Time Horizon refers to the expected time span that an individual requires before using investment returns. According to Droms and Strauss (as cited in Grable et al., 2009), the shorter an investor's *Time Horizon*, holding all other factors constant, the more conservative the investor should be when making financial decisions, i.e. the lower their *Risk-Tolerance.* As pointed out by Grable et al. (2009), investors with shorter investment *Time Horizons* lack the necessary time to recover losses in the event of a decline in portfolio value and therefore, they should have lower *Risk-Tolerance* levels. The opposite is true for investors with longer *Time Horizons*. Lewellen et al. (1974) found that individuals with larger emphasis on short-term capital gains display a greater willingness to take risks. Conversely, Mayfield et al. (2008) found that individuals with low levels of *Risk-Tolerance* do not engage in long-term investing. Harlow and Brown (1990) also suggested that portfolio managers

[13] A sample of five Coloured respondents was insufficient to warrant its inclusion as a racial category in the analysis.

often summarise *Risk-Tolerance* by examining the individual's *Time Horizon*, where longer *Time Horizons*, other things being equal, dictate higher *Risk-Tolerance*.
A plethora of financial management literature (Grable & Lytton, 1998; Roszkowski, Snelbecker, & Leimberg, 1993) and websites (such as Investopedia) support the aforementioned heuristics as mental short cuts to enable quick and efficient decision-making on behalf of the financial advisor. Whilst this might be helpful in some instances, it introduces room for error, especially in South Africa, where there are little studies devoted to empirically support (or reject) the use of these heuristics. Even in light of the evidence reported above, advisors should be cautious to use them indiscriminately. The above overview of the significant predictors of *Client Risk-Tolerance* only reports on studies that support the use of the most commonly used decision-making heuristics. However, it does not make reference to studies that produced disconfirming results, i.e. insignificant relationships or relationships that are in the opposite direction. Research regarding a few of the demographic/ socioeconomic variables are in fact fairly inconclusive. The results produced by these studies, as discussed in section 2.6.1, pointed towards the working of more complex and dynamic interactions between the variables. This study set out to examine these variables and the complex interactions between them so as to include them within the *Client Risk-Tolerance* conceptual model.

As Strydom et al. (2009) rightfully points out, many of the relationships (highlighed in the section above) are based on stereotypical, often harmful, beliefs and judgments. Financial advisors are tasked with the responsibility of collecting reliable and relevant information from investors in order to avoid the possibility of misclassifying investors into the wrong *Risk-Tolerance* categories. Correctly understanding the predictors of *Risk-Tolerance* is an important issue for finanical management if financial advisors are to optimise their service delivery. This research aims to provide valuable insight into the factors that affect *Risk-Tolerance*. The aim is to provide a better understanding of how individuals in South Africa make financial decisions and to assist financial advisors to provide financial advice that is tailored to suit the individual needs of investors. Toward this end, this research argues for the inclusion of *subjective risk judgment variables*, i.e. personality and emotion regulation, as an additional set of predictors when determining *Client Risk-Tolerance* levels. The following section will provide a definition of *subjective risk judgment*.

2.3.2 Subjective risk judgment

According to Hughes (2013) individuals show substantial heterogeneity in financial behaviour, which is defined as "any human behaviour that is relevant to money management" (Hughes, 2013, p. 4). Thus, it could be argued that this may also be the case for *Investor Risk-Tolerance*. At the core of this research lies the need to equip the financial advisor with a tool that will enable him/her to provide a personalised service that caters to the heterogeneous needs and characteristics of the client. In this regard, the importance of *Risk-Tolerance* as an input during the investment process has been stressed. *Risk-Tolerance* is a complex psychological construct that encompasses an individual's values, beliefs, personal goals, and desire to feel confident and in control (Callan & Johnson, 2002). This research is geared towards gaining a more in-depth understanding of the most significant predictors of an investor's level of *Risk-Tolerance*. Past research efforts aimed at understanding the predictors of *Risk-Tolerance* largely focuses on a range *objective risk-tolerance* factors. When applying the results obtained from studies that have a limited focus on demographic and socioeconomic factors, financial advisors run the risk of classifying investors into suboptimal *Risk-Tolerance* categories (Grable & Lytton, 1998) that does not align financial decisions or portfolio allocations with the individual's financial goals *and* personal preferences and needs.

It is acknowledged that many advisors most probably use assessment methods that incorporate questions relating to individual differences, i.e. personality. The robustness, i.e. psychometric reliability and validity, of these methods, however, is not always evident (Callan & Johnson, 2002). Inaccurate classification based on measures that are suboptimal may overexpose clients to risk, or deprive them from the level of risk that is optimal in terms of their unique needs and characteristics.

It is also important to take cognisance of the fact that clients often lack understanding about their financial "selves" and the financial risk that they are willing to take (Callan & Johnson, 2002). Further to this, investment discussions and financial planning may often lead to miscommunication, discomfort and at worst, stress and aggression, due to its technical nature. Therefore, discussions between the advisor and client should be focused around an explicit and understandable individual *Risk-Tolerance* score or profile (Callan & Johnson, 2002). A robust assessment of *Risk-Tolerance* may allow for a greater understanding of the individual and may facilitate a discussion whereby the individual is empowered to understand and appreciate the nature of an investment or financial decision.

Research that focus on introducing a comprehensive range of personal or individual differences factors will serve to contribute to a body of reliable and valid evidence that may improve the way in which *Risk-Tolerance* is determined, and in doing so improve the service delivery on the part of the advisor. This research argues that accuracy of assessment is crucial if advisors seek to provide advice that truly speaks to an individual's level of *Risk-Tolerance*, as a function of his/her unique needs and attitudes. Relying primarily on *objective risk-tolerance* factors, as predictors of *Risk-Tolerance*, or inadequately validated assessment methods could result in failure to accurately gauge the baseline degree of *Client Risk-Tolerance* by the financial advisor. This may lead to wrongfully matching a client's objectives with the investment or financial plan. This classification strategy could be costly in four respects (Grable, 1997; Roszkowski et al., 2009):

(a) clients may sell at a loss if incorrectly classified into a higher *Risk-Tolerance* category;
(b) clients may fail to meet their goals and objectives if wrongly classified into a lower *Risk-Tolerance* category;
(c) financial advisors risk their reputation as credible practitioners; and
(d) financial advisors risk the possibility of legal action that entail significant liability settlements.

It is argued in this research that there exists a major paucity in investor or financial *Risk-Tolerance* research studies, especially in South Africa. As will become evident later in this literature review, the few studies that are dedicated towards the subject matter firstly, mostly focus on *objective risk-tolerance* variables only and secondly, provide inconsistent and somewhat inconclusive results. As mentioned there has been a growing scepticism with regard to the ability of *objective risk-tolerance* variables to accurately and effectively explain and predict *Client Risk-Tolerance* (e.g. Grable, 1997; Grable & Joo, 1999; Harlow & Brown, 1990). Therefore, it is proposed in this research that the investigation of variables that determine *Client Risk-*

Tolerance should be expanded beyond the testing of purely *objective risk-tolerance* factors (i.e. demographic and socioeconomic factors) to include the influence of a second set of predictors, i.e. *subjective risk judgment variables,* on *Client Risk-Tolerance* in isolation, as well as in a complex dynamic interaction with each other, in order to better explain variance in *Client Risk-Tolerance.* For this to be achieved, however, an elaboration of the term *subjective risk judgment* is required. A definition of *subjective risk judgment* is construed in which *Risk-Tolerance* is conceptualised as a function of personal preference or willingness to assume risk.

According to Ricciardi (2004, p. 12) “risk is inherently subjective. In this view it does not exist out there, independent of our minds and cultures, waiting to be measured. Instead, human beings invented the concept of risk to help them understand and cope with the dangers and uncertainties of life. Although these dangers are real, there exists no such thing as objective risk”. Given the scant literature pertaining to the influence of personality and other psychological determinants (i.e. emotion regulation) on *Risk-Tolerance*, a definition of *subjective risk judgment* was constructed for specific use within this research.

Hanna and Chen (1997) proposed that *Risk-Tolerance* is a subjective function of risk and further argued that *Risk-Tolerance* has a genetic predisposition, i.e. it is related to personality traits. Furthermore, Van de Venter et al. (2012) conceptualised *Risk-Tolerance* as a function of an individual’s personal preference, i.e. the risk that an individual prefers to take. Based on these studies, the following definition of *subjective risk judgment* was developed for this study:

> “The level of risk that an individual prefers to take and is willing to accept given aspects of his/her personality and ability to self-regulate his/her emotions”.

Explained differently, it is argued that *subjective risk judgment* refers to differences in personality and ability to self-regulate emotion, which predisposes individuals to have certain feelings and make certain judgments with regard to perceived risk. At this point it is important to stress the difference between the two sets of predictors. That is, *subjective risk judgment* in this study refers to the willingness or preference to take risks, whereas *objective risk-tolerance* for the purposes of this research refers to the ability or capacity to bear risk.

2.4 Developing a Conceptual Model of Client Risk-Tolerance

The research initiating question asks why there is variance in *Risk-Tolerance* amongst clients in need of financial advice. In response to the research initiating question, the remainder of this literature study will attempt to present a theoretical argument based on the influence of both the categories of variables, i.e. *objective risk-tolerance* and *subjective risk judgment* variables, on *Client Risk-Tolerance.*

As the literature study unfolds, however, a lack of consensus and contrasting results will become apparent. Especially with regard to the *objective risk-tolerance* factors, the exact nature of their relationships with *Risk-Tolerance* in isolation, as well as in interaction with the *subjective risk judgment* factors, are very unclear. As was evident from the literature review, the majority of the studies, discussed in section 2.6.1, applied methods to examine the direct relationship of the various objective factors with *Risk-Tolerance*, in isolation. Some of the studies discussed in section 2.6.1 implied, but most studies failed to clarify the role of moderators within a more complex nomological net of predictor variables of *Client Risk-Tolerance*. Therefore, it is argued that it is precisely this constricted focus that could have led to the disparity and lack of comparable empirical evidence. Moreover, the general trends in the research literature (presented in section 2.6.1) suggests an indication of an extremely complex and dynamic interaction between *objective risk-tolerance* and *subjective risk judgment* factors within a nomological net – an interaction which has not yet, to the knowledge of the researcher, been empirically examined with SEM.

Given the pivotal role of personality and emotion regulation in determining the level of *Client Risk-Tolerance*, an objective of this study is to capture the nature of these presumed relationships in a comprehensive *Client Risk-Tolerance* conceptual model. In this study it is argued that the links between personality and emotion regulation, and *Client Risk-Tolerance* are complicated. It is argued that this complexity arises because these links are moderated by other aspects of the individual relating to demographic, as well as socioeconomic factors. Therefore, the ultimate aim of this study is to capture the presumed relationships in a comprehesive *Client Risk-*

Tolerance conceptual model, depicted in figure 2.2, which attempts to explain the manner in which the various personality and emotion regulation latent variables are moderated by the demographic and socioeconomic latent variables to affect overall *Client-Risk Tolerance*.

The *objective risk-tolerance* variables that have received considerable attention in previous research were selected for inclusion in the comprehensive conceptual model. They included: *Age, Gender, Education* and *Income*. With regard to the *subjective risk judgment* factors, as a result of the subsequent literature study, the Big Five personality traits *Extraversion, Conscientiousness, Openness to Experience, Agreeableness and Neuroticism*; as well as *Sensation Seeking, Delay of Gratification, Emotional Self-Management and Emotional Self-Control,* were included in the model.

Hence, the following section aims to provide an overview of research findings associated with each of the variables listed above. Firstly, an attempt will be made to argue for the inclusion of personality and emotion regulation variables in the conceptual model based on theoretical arguments and previous research findings within the domain of risky decision-making and behaviour. Secondly, demographic and socioeconomic factors as moderating variables will be explored. Studies are included in which relationships between demographic/socioeconomic variables and *Risk-Tolerance* were found, as well as where these associations were not confirmed. All of the available research is presented in an effort to come to a logical conclusion regarding the most probable propositions regarding the relationships between these variables and *Risk-Tolerance*. Twenty-seven hypotheses will be presented in total. The proposed relationships are depicted in the *Client Risk-Tolerance* conceptual model, depicted in figure 2.2. Fifteen of the hypotheses could be tested via structural equation modelling (SEM), and therefore related statistical hypotheses were stated in chapter 3. In line with this the first 15 hypotheses were assigned the LISREL notation according to the SEM convention[14] (in terms of ξ and η) and were captured in a reduced *Client Risk-Tolerance* structural model (figure 2.3). The remaining 12

[14] LISREL conventions dictate that each latent variable should have at least two observed variables, in order to be included in a structural model. The nature of the demographic and socioeconomic variables did therefore not lend itself to being included in the LISREL structural model in this way.

hypotheses could not be tested via SEM and were thus not assigned the LISREL notation, nor included in the reduced structural model. These hypotheses were tested with moderated regression.

2.5 Personality

Personality is central to the aims of this research. A growing body of research is devoted to the predictive power of personality traits with evidence suggesting its ability to predict a wide range of human behaviours and important life outcomes. Alternative definitions for personality has been devised by various scholars. According to Allport (1961) personality can be defined as “a dynamic organisation, inside the person, of psychophysical systems that create the person’s characteristic patterns of behaviours, thoughts and feelings” (p. 11). Funder (2004) defined personality as “an individual’s characteristic patterns of thought, emotion, and behaviour, together with the psychological mechanisms – hidden or not – behind those patterns” (p. 5). In addition to this Pervin, Cervone, and John (2005) described it as “those characteristics of the person that account for consistent patterns of feeling, thinking, and behaving” (p. 6); and according to Mayer (2007) personality can be defined as “the organized, developing system within the individual that represents the collective action of that individual’s major psychological subsystems” (p. 14).

Even in the absence of a uniform definition of personality, it is possible to extract the central themes inherent in most definitions, i.e. personality refers to relatively stable and enduring characteristics that describe an individual’s unique way of thinking, feeling and behaving. In a study of this nature these common themes hold value in that a central theme in this research pertains to whether a person’s unique way of thinking, feeling and behaving produce consistent individual differences in his/her level of *Risk-Tolerance*.

2.5.1 The Big Five personality traits

The Big Five and five factor model are often used interchangeably when referring to the personality traits *Openness to Experience, Conscientiousness, Extraversion, Agreeableness* and *Neuroticism* or *Emotional Stability*. Although some scholars claim some difference between the two models, this research will refer to them interchangeably focusing rather on the proposed relationship between each of the five traits and *Risk-Tolerance*.

The *Big Five Personality Model* is considered the most comprehensive and accepted measurement of personality (Mayfield et al., 2008) and has been confirmed by research as important in understanding risk-related concepts (Nicholson et al., 2005). More specifically, personality as defined by the Big Five taxonomy has been shown to be a causal factor of *Risk-Tolerance* (Nicholson et al., 2002). The five dimensions, as defined in table 2.2, have been derived from extensive statistical analysis and have been proven to remain stable across situations.

Table 2.2

Big Five trait description

TRAIT	DESCRIPTION
NEUROTICISM (N)	High scores indicate tenseness, moodiness, anxiety, and insecurity.
EXTRAVERSION (E)	High scores indicate assertiveness, sociability, talkativeness, optimism, and being upbeat and energetic.
OPENNESS (O)	High scores indicate an active imagination, aesthetic sensitivity, a preference for variety, intellectual curiosity, and broad cultural interest.
AGREEABLENESS (A)	High scores indicate altruism, personal warmth, sympathy towards others, helpfulness, and cooperation.
CONSCIENTIOUSNESS (C)	High scores indicate purposefulness, being strong willed, determination, organisation, reliability, and punctuality.

(Mayfield et al. 2008)

2.5.1.1 Openness to Experience

According to Charles and Kasilingham (2014) *Openness to Experience* measures the depth, breadth and variability in a person's imagination and desire for experience. Attributes that are commonly included in definitions and measurement of the factor are intellect, ingenuity, reflection, promptness, introspection, creativity, imagination, liberalism, curiosity and adventurousness (Akhtar & Batool, 2012; Charles & Kasilingham, 2014; Donnellan, Oswald, Baird, & Lucas, 2006). Individuals scoring high on this factor are open-minded, liberal and characterised by making themselves open to novel experiences and activities. They have a preference for novelty instead of familiarity and a tendency to experience deeper and more variable emotional states (Anic, 2007). In contrast to this, individuals who score low on *Openness to Experience* tend to be conventional, structured and conservative, and find comfort in the familiarity of the status quo (Charles & Kasilingham, 2014).

Due to their open-mindedness and desire for novel experience, individuals with higher levels of *Openness to Experience* are more inclined to engage in financial experimentation and they are likely to tolerate conditions of uncertainty and change. This serves as the motivation to participate in risk-taking activities. Moreover, it can be argued that their emotional sensitivity may serve to enhance the thrill and pleasure of engaging in risky decision-making. In a study examining the determinants of small equity investor's risk assumption attitudes (which is conceptually the same as *Client Risk-Tolerance*), Ali and Waheed (2013) found support for the latter, suggesting that these investors lean towards confident investment decision-making and are capable of engaging their active imagination when making the trade-off between risk and return. The study yielded a positive and significant relationship between *Openness to Experience* and investor risk assumption attitude ($\beta = 0.60$ and p-value = 0.000).

Financial management scholars humorously equate the risk-return trade-off with financial skydiving, arguing that some individuals willingly engage in this process without batting an eye, whilst others struggle to cope without a secure harness (Bhat, 2008; Brigham & Houston, 2011). Considering the defining characteristics of *Openness to Experience* alongside this metaphor, this research will argue that individuals with higher levels of *Openness to Experience* are more likely to display higher levels of *Client Risk-Tolerance*.

Hypothesis 1: *Openness to Experience* (ξ_1) has a positive linear effect on *Risk-Tolerance* (η_4).

2.5.1.2 Conscientiousness

Conscientiousness is a measure of goal-directed behaviour and the individual's control over impulses (Charles & Kasilingham, 2014), where highly *Conscientiousness* individuals have the ability and tendency to exert control over behaviour and impulses in order to follow socially prescribed norms and rules, as well as personal goals (Rustichini, De Young, Anderson, & Burks, 2012). This higher-order factor subsumes several lower order traits including self-discipline, self-efficacy, thoroughness, deliberation, and need for achievement. The more conscientious a person is, the more competent, dutiful, orderly, responsible and thorough (McCrae & Costa, 1991).

Given the definition of *Risk-Tolerance* proposed in this study, *Conscientiousness,* as defined above, can be argued to be antithetical and inversely related to *Risk-Tolerance*. It is argued in this research that an individual low in *Conscientiousness* will firstly be less deliberate (i.e. not thinking before acting) and hastier, without necessarily considering the consequences of his/her actions. Translated into the sphere of investment decision-making this would mean that such an individual would display a tendency to act immediately with less information regarding the performance of an investment. Secondly, inherent in the definition of *Conscientiousness* are the concepts of control and conformity. According to Nicholson et al. (2002) and Nicholson et al. (2005) individuals with lower levels of *Conscientiousness* are less likely to experience the cognitive barriers associated with the need for control and conformity. Therefore, it is argued that investors with lower levels of *Conscientiousness* are more likely to tolerate uncertainty or investment return volatility.

Thirdly, achievement striving, i.e. the need to master difficult challenges and to meet high standards of excellence, and self-efficacy, i.e. the strength of an individual's belief in his/her own ability to complete tasks and reach goals, are inherent in the definition of *Conscientiousness*. These characteristics will reveal the individual's disposition towards how much he/she is willing to subject him or herself to potential personal or financial loss or damage when confronted with uncertain circumstances or conditions. However, consideration needs to be given to what constitutes high standards of excellence when confronted with financial decision-making. Does it constitute the relentless pursuit of high returns (despite high risk) or does it refer to more moderate, but secure (i.e. less risky) gains over the long-term? When adopting the prior definition of financial excellence one would argue that such individuals are possibly less conscientious due to their decreased need for control and certainty. Thus, it is not to say that such individuals are less achievement striving. In this research it is argued that the mechanisms through which achievement striving manifests are different. Thus, less conscientious individuals may be achievement striving, however flexible in their attempts and not constrained within the confines of control, and thus more impulsive and easier to persuade from one decision to another. The converse is true for highly *Conscientiousness* individuals, where there is a desire for achievement under conditions of control and certainty (Nicholson et al., 2002; Nicholson et al., 2005). These individuals would typically prefer and subsequently strive toward obtaining moderate, but secure gains in the long-term. In support of this, Pan and Statman (2010) argue that conscientious individuals have a propensity for maximisation, i.e. they dislike settling for second best. However, they also have the propensity for regret, i.e. they tend to ruminate over their initial choices and express doubt that a better choice could have been made (Pan & Statman, 2010). Poor financial choices open the door to regret which may lead to lower *Risk-Tolerance* levels.

Given the aims of this research, it is argued that conscientious individuals tend to plan and think cautiously before acting and making investment decisions that contain a considerable amount of risk. Instead of accepting higher risk investments out of a desire for quick financial prosperity, these individuals are more likely to gather significant amounts of information over time and concentrate on limited, but purposeful investment. In this research it is argued that conscientious individuals actively strive towards the avoidance of negative consequences, i.e. potential financial loss or damage, in order to preserve a sense of competence, duty and self-discipline.

Hypothesis 2: *Conscientiousness* (ξ_2) has a negative linear effect on *Risk-Tolerance* (η_4).

2.5.1.3 Extraversion

Extraversion is a measure of an individual's adventurous, assertive, frank, sociable and talkative tendencies. Extraverted individuals have a desire for excitement and a generalised need for stimulation, which could supply the motivation to take risks when making financial decisions (Anic, 2007, Nicolson et al., 2005). As defined in table 2.2, extraverted individuals generally possess dispositional optimism. In the financial management paradigm, typical descriptions of optimism include an individual's tendency to rate themselves as being less at risk than their peers and the tendency to expect a lower probability of negative outcomes (Balasuriya, Muradoglu, & Ayton, 2010). Optimistic individuals generally display a higher propensity to undertake risk (Belcher, 2007) and will continue to remain confident about the future even in the face of negative events such as financial loss or damage, because they attribute the event to an external cause.

In line with this reasoning, Pan and Statman (2010) have found that overconfidence (i.e. perceiving the range or variance of possible outcomes as narrower than it truly is) is pronounced among individuals with high *Extraversion*. This generalised tendency towards confidence may lead them to generally perceive risk as lower than their less confident counterparts. Based on these arguments, it is possible to conclude that these individuals will be more confident in their own ability to make investment decisions with above-average returns and therefore, it is predicted in this research that *Extraversion* will be positively related to *Risk-Tolerance*.

Hypothesis 3: *Extraversion* (ξ_3) has a positive linear effect on *Risk-Tolerance* (η_4).

A significant correlation between *Extraversion* and *Sensation Seeking* (which will be discussed later) has also been reported (Aluja, Garcia, & Garcia, 2003). This can be ascribed to the fact that the excitement-seeking facet of *Extraversion* is conceptually related to *Sensation Seeking*, which has been shown to be a key facet of personality that predicts *Risk-Tolerance*. Costa and McCrae (1992) defined excitement-seeking individuals as individuals who have a desire for excitement and stimulation. In this research it is argued that the higher individuals move along the *Extraversion* continuum, i.e. an increased adventurous propensity and tendency to seek excitement inducing opportunities or experiences, the more likely they are to be sensation seekers, i.e. individuals who seek these opportunities or experiences as an end in itself.

Hypothesis 4: *Extraversion* (ξ_3) has a positive linear effect on *Sensation Seeking* (η_1).

2.5.1.4 Agreeableness

Agreeableness can be defined as the desire to be cooperative and agreeable individuals possess a general concern for the well-being of others (Anic, 2007). Other attributes commonly included in the definition and measurements of this higher-order factor are altruism, nurturance, and care (Charles & Kasilingham, 2014), as well as trust, sympathy and modesty (Donnellan et al., 2006). With descriptors, that are mainly interpersonally directed, it is difficult to obtain a grasp as to how this factor should relate to personal *Risk-Tolerance*. However, scholars posit that an understanding of the opposite end of the continuum, i.e. low *Agreeableness*, could provide a better understanding. Low *Agreeableness* is associated with a robust self-interest and indifference toward others (Charles & Kasilingham, 2014), which are often desirable qualities when engaging in risky decisions or behaviours. It can be argued that it is the self-interest and indifference of these individuals that provide a buffer against the possible regrets associated with financial decision-making.

On the contrary it is possible to argue for the opposite effect, i.e. that high *Agreeableness* leads to higher *Risk-Tolerance* as these individuals are easily influenced by others and thus, persuaded by financial advisors. In line with the condition provided in the definition of *Risk-Tolerance* that high risk-tolerant individuals act on less information when making financial decisions, individuals low in *Agreeableness* are prone to making financial decisions based on information that is easily obtainable in the market and therefore, more susceptible to what is termed in finance literature as *herd behaviour*. According to Peterson (2016) *herd behaviour* is characterised by a lack of individual decision-making or thoughtfulness, causing people to think and act in the same way as the majority of those around them. In finance, a herd instinct would relate to instances in which individuals gravitate toward certain investments, based almost solely on the fact that many others are making the same or similar investment decisions. Thus, given the core attributes of cooperation and flexibility, it is argued that agreeable individuals may be more willing and likely to accept risk and tolerate uncertainty.

Hypothesis 5: *Agreeableness* (ξ_4) has a positive linear effect on *Risk-Tolerance* (η_4).

2.5.1.5 Neuroticism

Neuroticism or its antithesis, *Emotional Stability*, reflects an individual's general tendency to experience negative affective states (Lee, Krauessl, & Paas, 2010) and his/her level of emotional control (Charles & Kasilingham, 2013). *Neuroticism* includes characteristics such as negative affectivity, self-consciousness, physiological reactivity and behavioural inhibition (McCrae & John, 1992).

Neurotic individuals are prone to respond to stressful situations with intense, often unpleasant emotions, such as nervousness, worry, fear and anxiety (Anic, 2007; Charles & Kasilingham, 2014, Lee et al., 2010; Reiss, 1997). In terms of what this research is trying to predict, it is possible to argue that the trade-off between risk and return, and the accompanying uncertainty when making a financial decision, creates a potential stressful event to the neurotic individual. This argument is based on a finding by Nicholson et al. (2005) that among the facets inherent to *Neuroticism*, anxiety was strongly related to overall risk taking. According to Lauriola and Levin (2001) the propensity to experience anxiety may lead to the overestimation and consequent avoidance of risk. Similarly, Gasper and Clore (1998) argue that these individuals have an attentional bias toward threatening information, producing a biased risk perception and a generalised over-estimation of the risk associated with a financial decision. In contrast to this, it is argued that emotionally stable individuals may have superior coping abilities under conditions of stress and uncertainty. According to Nicholson et al. (2002) and Nicholson et al. (2005) lower levels of *Neuroticism* supply the insulation against regret and anxiety about negative consequences – something that often accompanies investment decisions in the form of lower realised versus expected return.

Given the above definition of *Neuroticism* as it relates to *Risk-Tolerance*, it is fairly safe to infer that these individuals may prefer situations that (a) produce lower chances of loss and thus, take comfort in lower-risk investments (knowing that there is a lower but more certain return), (b) require more information regarding the performance of an investment, and (c) tolerate less uncertainty.

Hypothesis 6: *Neuroticism* (ξ_5) has a negative linear effect on *Risk-Tolerance* (η_4).

A few empirical studies support the relevance of the Big Five in predicting *Client Risk-Tolerance*. For instance, a study by Nicholson et al. (2005) on a sample of 2 401 students and executives attending graduate courses at a local university using the Risk Taking Index (a measure of risk-taking in the domains of health, career, recreation, finance, safety and social risk) revealed the following results: *Extraversion* ($\beta = 0.26$, $p < .001$) and *Openness* ($\beta = 0.36$, $p < .001$) were positively related to risk-taking, while *Neuroticism* ($\beta = -0.18$, $p < .001$), *Agreeableness* ($\beta = -0.31$, $p < .001$) and *Conscientiousness* ($\beta = -0.20$, $p < .001$) were inversely related to risk-taking.

Lauriola and Levin (2001) examined the relationship between the traits included in the Big Five Model and choice behaviour in an experimentally controlled risky decision-making task. Risk was measured in trials where subjects were forced to choose between two choices, one that offered a sure gain (or loss), and a risky one that offered a potential gain (or loss) and stated the probability of that outcome. Their study revealed that low levels of *Neuroticism*, i.e. *Emotional Stability*, and high levels of *Openness* to *Experience* were related to higher propensity to take risks. Furthermore, they found a positive, but non-significant relationship between *Extraversion* and risk-taking.

2.5.2 Beyond the five factor model/Big Five

The five factor model is seen as relatively inclusive and has been used numerous times to predict a variety of behaviours, including economic behaviour. However, even though the mapping of personality onto the five factor model is largely regarded as the most accurate and all-encompassing model in literature, its use is not without dispute and various scholars have raised methodological and theoretical concerns with regard to its factor structure.

One such concern relates to the question of whether the five factor model is exhaustive of the personality sphere. Towards this end, a study conducted by Hughes (2013) has made a significant contribution. An extensive literature review revealed that there is a lack of coverage in the five factor model in the sense that numerous narrow traits are missing. This finding is not only important for descriptive purposes, "but also in terms of understanding and predicting behaviour. Traits exist beyond the reach of the five factor model that are hypothetically useful when understanding financial behaviour" (Hughes, 2013, p. 49).

In this research a similar stance is adopted and accordingly it will be argued that increased explanatory power can be gained from the assessment of certain lower-order traits, as the broad factors that are supposed to subsume the lower-order factors do not always show perfect correlations with them. A significant amount of variance can be left unexplained for due to the fact that many of the most salient lower-order factors get lost within the broader structures. According to Hughes (2013) broad factors represent only the variance common to all of their constituent traits and thus, trait-specific variance that could offer incremental prediction is lost. Hughes (2013) further argues that broad measures of personality is likely to lead to underestimated relationships and that the reliance on any single broad omnibus measure of personality (even focusing at the facet level) is likely to lead to the exclusion of a number of potentially relevant predictor traits.

However, to administer tests that are inclusive of all known lower-order personality traits would present a tedious task. Therefore, a review of literature relating to financial risk-taking was conducted in order to shed light on the most salient variables that will maximise the prediction and understanding of *Client Risk-Tolerance*, above those included in the Big Five model.

In the next section, personality traits hypothesised to be important in the prediction of *Risk-Tolerance* will be proposed on the grounds of its theoretical salience and ability to statistically maximise the relationship between personality and financial behaviours. The value of this approach lies in the fact that no other study, to the knowledge of the researcher, has collectively considered all of the proposed traits in a conceptual model.

2.5.2.1 Sensation Seeking

Sensation Seeking is a personality factor that has consistently been found to correlate with risk-taking behaviour (Blaszczynski et al., 1986; Corter & Chen, 2006; Wong & Carducci, 1991; Young et al., 2012). *Sensation Seeking* is a biologically based personality trait and Zuckerman defines sensation seekers as individuals "who seek varied, novel or complex sensations or experiences" (Blaszczynski et al., 1986, p. 113). These individuals are prepared to take physical, social, legal and financial risks primarily for the sake of such experiences (Corter & Chen, 2006; Lauriola & Levin, 2001; Wong & Carducci, 1991), regardless of the potential risky consequences that may follow. *Sensation Seeking* is generally conceptualised as encompassing four main concepts, i.e. thrill and adventure seeking, disinhibition, boredom susceptibility and experience seeking. According to Hughes (2013) these individuals exhibit a preference for intense, novel and arousing stimuli and because they quickly become bored with routine, are continually in search of ways to increase stimulation via exciting and often risky activities, behaviour, experiences and attitudes. Given that financial risk, i.e. risk related to loss of income or a portion of one's financial capital, is inherent in the definition of *Sensation Seeking*, it is argued that high sensation seekers appraise risk as less threatening and anticipate arousal as more positive than low sensation seekers. Various studies have succeeded in reporting significant associations between *Sensation Seeking* and risk taking, including compulsive gambling and every day financial matters.

For example, Harlow and Brown (1990) conducted a study on 183 students to determine the influence of biochemical and psychological factors on *Risk-Tolerance*. They reported significant relationships between financial *Risk-Tolerance* and *Sensation Seeking*, and its many forms, including general sensation-seeking, thrill and adventure-seeking, experience-seeking, disinhibition, and boredom susceptibility. More specifically they found that low levels of *Sensation Seeking* were associated with lower *Risk-Tolerance*.

Similarly, Wong and Carducci (1991) theorised that the heightened level of arousal and stimulation desired by high sensation seekers is created by the risks associated with gambling, with high sensation seekers betting at higher odds in comparison to low sensation seekers. They extended the research limited to the gambling-domain to include everyday financial matters, such as investment risk and household affairs risk. In a sample of 233 undergraduate students, they found that the aforementioned trend (i.e. greater financial risk-taking tendencies exist in high sensation seekers) could be extended to everyday financial matters. Moreover, a study by Zuckerman and Kuhlman (2000) that examined the relationship between personality and risk-taking, found *Sensation Seeking* as a personality trait highly relevant to the prediction of risk-taking.

Hypothesis 7: *Sensation Seeking* (η_1) has a positive linear effect on *Risk-Tolerance* (η_4).

2.5.2.2 Self-regulation

Self-regulation can be defined as the ability or willingness to enact restraint in order to suppress, modify, and adapt one's emotions, impulses or desires to act or respond in accordance with the situation [i.e. to behave in accordance with social norms, rules or laws and to avoid negative consequences (Howlett, Kees, & Kemp, 2008; Hughes, 2013)]. Thus, low self-regulatory control may lead to manifestations of behaviours such as risk-taking and careless decision-making due to an inability to control emotions, impulses and desires.

Two specific forms of self-regulation will be proposed as meaningful predictors of *Client Risk-Tolerance* in the subsequent sections. The first form is the lower-order personality trait, *Delay of Gratification*. The second form is derived from the emotional intelligence domain and is called emotion regulation.

2.5.2.2.1 Delay of Gratification

Another trait not measured by the omnibus Big Five is deferred or delayed gratification. According to Hughes (2013, p. 74) *Delay of Gratification* refers to "a sensitivity to reward that is manifest in the willingness/ability to pass up enjoyment or something of value now with the aim of achieving something of greater enjoyment or value in the future". The inability to delay gratification is associated with the tendency of individuals to sacrifice long-term goals in favour of short-term goals, allowing them to experience an immediate gratification (Tice & Bratslavsky, 2000). According to Shamosh and Gray (2008) this concept is useful for studying self-control due to its reliable and stable assessment over time.

This trait is of importance for the aim of this study considering that any investment decision in essence is based to a large extent on the willingness/ability to forego an immediately rewarding outcome for an outcome at some future point in time. For example, many investors may act only upon more cautious, information gathering in order to experience greater certainty, which leads to investing more systematically and strategically. These investors prefer smaller or more modest rewards in the present in order to accumulate the sum of more modest rewards in future and therefore have a superior ability to delay gratification. As Hughes (2013) point out, individuals who have the ability to delay gratification are often those individuals who are frugal and exhibit financial prudence. In contrast, individuals who fail or are less able to delay gratification are hypothesised to lack the necessary planning skills and deliberation. They are likely to act imprudently, failing to consider the future consequences of their immediate actions or decisions, and will invest in a riskier manner.

It is argued that individuals who display the ability to delay gratification show a greater appreciation for the long-term consequences associated with risky financial decisions. Further to this, it is argued that these individuals may be more willing to make lower-risk financial decisions as a means of securing a certain financial reward in the future, at the expense of a higher but uncertain reward with larger probable losses.

Hypothesis 8: *Delay of Gratification* (η_3) has a negative linear effect on *Risk-Tolerance* (η_4).

Individual differences in the higher-order traits, i.e. the Big Five/five factor model traits, have been associated with the ability to delay gratification. For example, *Extraversion* is associated with a dispositional sensitivity to potential rewards. A study conducted by Hirsh (2015) on savings rates in extraverted populations argued that extraverted individuals have a heightened sensitivity to immediate rewards (due to a responsive dopaminergic system which serves as the brain's reward system) and tend to be less responsive to delayed rewards. During intertemporal choices (i.e. the relative value that people assign to two or more payoffs at different points in time), the dopaminergic system drives the preference for immediate gratification such that immediate rewards become more salient to extraverts when compared to long-term gains. Thus, these individuals discount rewards more steeply than introverts (Hirsh, 2015). It has also been hypothesised that extraverts have a stronger desire or value for high quality lifestyles and thus, an increased appetite for immediate consumption in fulfilment of that goal. Naturally, this may lead them to make riskier and often ill-calculated investment decisions based on the prospect of obtaining a higher return.

Translated to the aims of this research, it is argued that extraverted individuals make less deliberative financial decisions, i.e. act on less information and planning as per definition of *Risk-Tolerance*, based on their dispositional preference for immediate gratification.

Hypothesis 9: *Extraversion* (ξ_3) has a negative linear effect on *Delay of Gratification* (η_3).

Successful delayers can also be described as being open to experience. The basis for this argument resides in the ability of such individuals to divert attention inward and away from potentially tempting and frustrating aspects of the immediate environment (Mischel, Shoda, & Peake, 1988). McCrae and Costa (1987) described *Openness to Experience* as encompassing the tendency to have a rich inner life and to experience the world in unusual and creative ways. Therefore, it could be argued that such individuals are able to avoid focusing on the possibility of an immediate reward by thinking about future rewards in more abstract means.

Openness to Experience is further associated with delayed gratification through its reliable association with intelligence. That is, open individuals tend to display superior scores on tests of cognitive ability (Hirsh, 2015). Intelligence is deemed an important factor in delayed gratification, with greater cognitive ability predicting preferences for larger delayed rewards over smaller immediate rewards (Hirsh, 2015; Shamosh & Gray, 2008). As intelligence increases, individuals display increasing tendencies toward planning, foresight, and *Delay of Gratification*, all of which are relevant for the aims of this research in terms of the definition of *Risk*-Tolerance. That is, lower risk tolerant individuals will act upon deliberate planning and information gathering when engaging in financial decision making and thus intelligence is linked to lower levels of *Risk-Tolerance*.

Hypothesis 10: *Openness to Experience* (ξ_1) has a positive linear effect on *Delay of Gratification* (η_3).

Successful delayers may also be described as conscientious. It is possible to argue that the ability to sacrifice an immediately rewarding activity in pursuit of another (presently less desirable) activity that is likely to produce a greater reward in the future, often requires the will to achieve and a sense of self-discipline – qualities which are inherent in the definition of *Conscientiousness*. Individuals with higher scores on *Conscientiousness* are described as strong willed, determinant and purposeful (table 2.2) and therefore, it can be argued that such individuals could have the superior ability to forgo immediate gratification in pursuit of systematic and strategic longer term investments.

Hypothesis 11: *Conscientiousness* (ξ_2) has a positive linear effect on *Delay of Gratification* (η_3).

2.5.2.2.2 Emotion regulation

According to Tice and Bratslavsky (2000), emotion regulation is a specific form of self-regulation that involves overriding one set of emotion responses with another, incompatible set of emotional expressions or experiences. Emotion regulation refers to the processes by which control over the type and intensity of emotions that individuals experience and express is exerted (Gross, 1998).

Moreover, emotion regulation falls within the broader framework of emotional intelligence, which is defined as the ability to purposely adapt, shape and select environments through the use of emotionally relevant processes (Gignac, 2010). According to Gignac (2010), emotional intelligence consists of seven underlying dimensions. Two of these dimensions can also be regarded as constituting the underlying dimensions of emotion regulation, i.e. *Emotional Self-Management* and *Emotional Self-Control*. Accordingly, the hypothesised effects will independently refer to these two dimensions.

Emotional Self-Management measures the relative frequency with which individuals manage their own emotions successfully. *Emotional Self-Management* is concerned with moving on from an emotional setback as opposed to dwelling or ruminating over a situation. It generally focuses on the ability to successfully adjust to negative emotional states with some focus on engaging in activities that maintain positive emotional states. *Emotional Self-Control* measures the relative frequency with which individuals control their strong emotions appropriately. The focus is placed on noticeable maintenance of focus in the face of emotional adversity. This, in contrast to *Emotional Self-Management,* concerns a behavioural demonstration of controlling intense reactive emotions. Other scholars have defined emotion regulation in terms of the underlying strategies that constitute it. According to Heilman et al. (2010) the dimensions of emotion regulation are antecedent-focused and response-focused emotion regulation. *Emotional Self-Management* is similar to antecedent-focused emotion regulation due to its proactive nature, whereas the reactive nature of *Emotional Self-Control* is more aligned with response-focused emotion regulation.

The literature also makes reference to two sub-strategies that relate to the aforementioned dimensions (i.e. response and antecedent-focused). Firstly, cognitive reappraisal is an antecedent-focused emotion regulation strategy in which the route of emotional responses is altered through reforming the meaning of a situation. Secondly, expressive suppression is a response-focused emotion regulation that inhibits behaviours associated with emotional responding. A further distinction can be drawn between the two sub-strategies, i.e. reappraisal diminishes emotions at an early stage with no need for prolonged effort, whereas suppression requires an active effort to inhibit potent emotional responses (Heilman et al., 2010). Consequently, it is possible to draw the link between *Emotional Self-Management*, as a proactive form of emotion regulation, and cognitive reappraisal, and *Emotional Self-Control*, as a reactive form of emotion regulation, and expressive suppression.

In a study examining the effects of emotion regulation on decision-making under risk and uncertainty, Heilman et al. (2010) reported that emotion plays a key role in both social and economic decision-making. Heilman et al. (2010) further argued that human beings could anticipate the emotional impact of a potential future decision using the process of emotion regulation. In line with literature regarding the link between personality and risk-taking, they found that emotions associated with anxiety increase risk aversion, i.e. reduce *Risk-Tolerance*, and impair optimal decision-making.

The use of reappraisal is considered effective in decreasing stimulation related to anticipation of reward and loss aversion. More specifically, reappraisal enables riskier decision-making by effectively down regulating negative emotional experience (Heilman et al., 2010). Similarly, Sokol-Hessner et al. (2012) argued that the regulation of emotion, through reappraisal-focused strategies, reduces risk aversion. Whilst the effect of suppression on risk aversion induced by negative emotions were initially contested (due to the hypothesis that it cannot decrease the experience of negative emotions, but only mask it), Heilman et al. (2010), nonetheless, found that reappraisal and suppression both have the ability to control positive emotions and can therefore decrease risk aversion. A similar stance will be adopted in this research arguing that some emotional control under adverse or uncertain circumstances is better than no emotional control. More specifically, the use of *Emotional Self-Control* may allow for the control or suppression of strong positive or negative emotions associated with risky financial decision-making and may therefore decrease risk aversion. It endows the individual with the ability to stay focused and provides a sense of rationality when making decisions that are initially emotionally laden (Gignac, 2010). Based on these findings, it is therefore hypothesised that both *Emotional Self-Management* and *Emotional Self-Control* may enable an individual to engage in riskier financial decision-making.

Hypothesis 12: *Emotional Self-Management* (η_2) has a positive linear effect on *Risk-Tolerance* (η_4).

Hypothesis 13: *Emotional Self-Control* (ξ_6) has a positive linear effect on *Risk-Tolerance* (η_4).

Given the widely acknowledged correlations between *Neuroticism* and negative affect or emotional experience, and *Extraversion* and positive affect or emotional experience, and the aforementioned relationships between emotion regulation variables and affect, an additional argument is that personality differences with regard to emotion regulation exist. That is, personality differences exist in the process by which individuals control the type and intensity of emotions that they experience and express (Ng & Diener, 2009). Robust relationships are documented in correlational studies, where neurotic individuals react more strongly to negative stimuli and extraverted individuals react more strongly to positive stimuli. As mentioned under their respective sections it is such individual differences that my lead to an increase or decrease in *Risk-Tolerance.* An additional line of reasoning is that personality traits are related to emotional experience, by means of emotion regulation (Dynes, 2010; Ng & Diener, 2009).

Trait-congruency theory proposes the individual tendency to process trait-congruent emotional information (Rusting, 1998). For example, extraverts process and recall positive stimuli faster and better, and are more likely to interpret ambiguous stimuli positively. Neurotic individuals process and recall negative stimuli faster and better and are more likely to interpret ambiguous stimuli negatively (Ng, 2007). Individuals are motivated to experience and maintain trait-congruent emotions and to avoid or change trait incongruent emotions. In a study conducted by Ng and Diener (2009) the tendency to reduce or eliminate negative emotions or turn them into positive ones (i.e. *Emotional Self-Management*) correlated positively with *Extraversion*. Moreover, *Extraversion* was related to the ability to preserve or savour positive emotions (i.e. *Emotional Self-Management*). In contrast to this the tendency to reduce or eliminate negative emotions or turn them into positive ones negatively correlated with *Neuroticism*. *Neuroticism* was associated with maladaptive emotion regulation strategies where neurotic individuals made lower use of strategies to repair negative emotions (Ng & Diener, 2009). Other scholars have provided support for this. For example, Dynes (2010) stated that neurotic individuals experience more negative mood states than emotionally stable individuals in part due to ineffective problem-solving and poor emotion regulation skill use. Lauriola and Levin (2001) suggested that neurotic individuals tend to focus on negative consequences while emotionally stable individuals are more apt in accepting such negative consequences. Thus, an emotionally stable individual is more likely to change or eliminate the experience of negative affectivity related to risky and uncertain choices. In this research an association will be drawn between the individual's standing on the variables, *Neuroticism* and *Extraversion*, and his/her ability to effectively engage in reappraisal-focused or *Emotional Self-Management* strategies. In light of the proposed relationship between reappraisal and riskier decision-making (where reappraisal leads to effectively down regulating negative emotion experience), it is possible to argue that the effect of personality on *Risk-Tolerance* may be mediated by emotion regulation, more specifically *Emotional Self-Management*.

In conclusion, these findings lead to the argument that individual differences (i.e. *Emotional Stability* and *Extraversion*) in *Risk-Tolerance* are mediated by *Emotional Self-Management*.

Hypothesis 14: *Extraversion* (ξ_3) has a positive linear effect on *Emotional Self-Management* (η_2).

Hypothesis 15: *Neuroticism* (ξ_5) has a negative linear effect on *Emotional Self-Management* (η_2).

2.6 Demographic and Socioeconomic Variables

2.6.1 Gender and Risk-Tolerance

The assumption that men generally should, and do, take more financial risks than women continues to take credence within the investment/financial management community. Much research has been devoted to studying gender differences with regard to financial *Risk-Tolerance*; however, few scholars have pursued to theoretically explain and examine why such differences exist. The majority of scholars provide explanations commonly based on stereotypical personality differences between men and women, i.e. masculine and feminine traits. Whilst this holds merit, as it has been shown on numerous instances that individual differences in personality correlates with gender (Helson, Jones, & Kwan, 2002; Roberts, Caspi, & Moffit, 2001; Wink & Helson, 1993), it will be argued in this research that given certain fixed levels of personality and emotion regulation, *Risk-Tolerance* will vary depending on an individual's *Gender*. In other words, when two individuals have the same standing on the latent variables, personality and emotion regulation, the effect of those variables on *Risk-Tolerance* will vary as an individual's standing on the variable *Gender*, i.e. male or female, varies.

The argument for the inclusion of *Gender* as a moderating variable (as with all the subsequent demographic and socioeconomic variables) will be based on the inconclusiveness of previous research findings. The inconsistent results produced by the studies discussed hereunder may be due to the fact that *Gender* interacts with personality and emotional regulation (which is hypothesised to have a stable and direct effect on *Risk-Tolerance*) to produce varying levels of *Risk-Tolerance*. If differences in *Risk-Tolerance* could be ascribed to the fact that male and female investors differ in terms of personality, it is argued that the results should possibly have been more consistent. Thus, an individual's standing on the *Gender* variable might either strengthen or weaken the relationship between personality and emotion regulation variables, and *Risk-Tolerance*. Subsequent arguments will be based on findings in literature that relate to differences in the way that men and women process information as well as *Gender* role expectations and socialisation. However, the conflicting results will be unpacked first.

As indicated there is a large amount of research, both empirical and anecdotal, to suggest that this relationship really does exist and that *Gender* can be used effectively as a classification of investors into different *Risk-Tolerance* categories. According to Graham, Myers, and Stendardi (2002) *Gender* is the third most powerful determinant of investing, after *Age* and *Income* has been considered. However, as will become evident in the proceeding summary of prevailing research studies, the results are fairly blurry, with some scholars proposing positive relationships and others vouching for a negative relationship or no relationship at all.

Studies are included in which relationships between *Gender* and *Risk-Tolerance* were found, as well as where these associations were not confirmed. All of the available research is presented in an effort to come to a logical conclusion regarding the most probable propositions regarding the relationship between *Gender* and *Risk-Tolerance*[15].

Earlier studies conducted in the 1990's revealed that males generally display a greater tendency toward risk-taking and therefore, they are more risk-tolerant than females (Batjelsmit & Bernasek, 1996; Hawley & Fujii, 1994; Wong & Carducci, 1991). Consistent with earlier findings regarding gender differences, Olsen and Cox (2001), within the context of professional investing, found that female professional investors were more risk averse than male professional investors. Moreover, studies by Hallahan et al. (2003) and Hallahan et al. (2004) examining the relationship between subjective financial *Risk-Tolerance* and a range of demographic characteristics found *Gender* to be an important differentiating factor in the classification of *Risk-Tolerance* (when all variables were entered into a hierarchical regression analysis model). Males exhibited a significantly higher tolerance for risk when compared to otherwise demographically equivalent female counterparts. A study by Croy et al. (2010) revealed that women tend to choose more conservative investment strategies and were found to hold fewer risky financial assets.

However, results from a study by Blum (1976) in which respondents were asked to assume that they had received a sum of money equal to one year's income, but under the condition that the money must be invested rather than spent, and that they must choose one of four investments, revealed that there were no statistically significant difference between male and female standing on *Risk-Tolerance.* Moreover, a comprehensive study by Palsson (1996) using a logit regression and Swedish cross-sectional data based on 1985 tax returns from more than 7 000 households, concluded that *Risk-Tolerance* did not systematically change according to *Gender*. Schubert et al. (1999) found that there was no significant *Gender* difference in financial *Risk-Tolerance* under controlled experimental economic conditions. Further studies by Grable and Joo (1999) and Hanna et al. (1998) also

[15] The same framework will apply to the subsequent demographic and socioeconomic variables *Age*, *Income* and *Education*.

arrived at the conclusion that *Gender* was not significant in predicting financial *Risk-Tolerance*. From the aforementioned it is evident that research results are largely inconclusive on the effect of *Gender* on *Risk-Tolerance*.

The *Selectivity Model* or hypothesis, as proposed by Meyers-Levy in 1989 (Arcand & Nantel, 2005), holds that males and females differ with regard to their information processing style, i.e. they select different cues from the environment when processing information. Graham et al. (2002) posited that the *Selectivity Model* is useful in explaining differences in financial decision-making by males and females as they are likely to perceive financial information differently and thus, base their decisions on differing perceptions.

Males are what are termed selective processors. They do not engage in comprehensive processing of all available information in the external environment (Arcand & Nantel, 2005). Instead, they reorganise the processing of external information by focusing mostly on self-relevant information, which then acts as heuristic devices that drive decision-making or judgments. It is argued that men pay attention to the cues that are the most available, the most salient to them and the most salient within a specific context. Men are less likely to pay attention to subtle, often disconfirming details. By contrast females are comprehensive processors meaning that they meticulously process information. They are more likely to assimilate all available information, engage in effortful and piecemeal analysis of such information, and have a lower threshold for noticing the subtleties (Arcand & Nantel, 2005). A lower threshold means that the level at which a stimulus is of sufficient intensity to produce an effect is lower and thus females are likely to respond quicker and more intensely to subtleties and disconfirming information.

Evidence from clinical studies supports this difference by suggesting that *Gender* differences with regard to information processing are related to differences in brain laterisation. According to Arcand and Nantel (2005) males rely on right-hemisphere processing, denoted by a reliance on global rules. Females on the other hand rely on left-hemisphere processing, which relates to specificities and intricacies represented by stimuli. These hemispheric differences support the holistic undifferentiated processing style of males and the detailed and elaborated processing style of females (Arcand & Nantel, 2005).

The selectivity can manifest itself in various ways – *Risk-Tolerance* being one of them. For example, in explaining men's higher propensity to take risk, the *Selectivity Model* proposes that since men consider the most salient cue, they are more likely to focus on task effectiveness of a return on investment without considering risk because it does not converge to a single inference (Arcand & Nantel, 2005). In contrast, women as detailed processors will consider all available information available including subtle and potentially disconfirming information. Women are thus more likely to incorporate risk and other secondary information when making financial decisions (Graham et al., 2002).

Another line of reasoning relates to gender roles and socialisation, i.e. men and women are differentially socialised in terms of money. According to Garrison (2010) *Cognitive-Social Learning Theory* of risk-taking behaviour suggests that social factors in combination with personality have a greater effect on various forms of risk-taking.

For example males are traditionally socialised as breadwinners and supporters. The financial implications are obvious in that men often have greater experience with, and control over finances, and are also more likely to rank personal finance as important. In contrast to this, females are socialised as homemakers and caretakers (Qiao, 2012) and subsequently, they are often placed in positions unrelated to financial decision-making and receive less exposure.

Based on the line of reasoning posited above, it will be argued that *Gender* moderates the relationship between *Conscientiousness* and *Risk-Tolerance, Agreeableness* and *Risk-Tolerance*, as well as *Neuroticism* and *Risk-Tolerance.* More specifically, given that conscientious individuals are more deliberate and prudent when making financial decisions, giving full consideration to the consequences of their actions, it is argued that this effect will be strengthened by a woman's comprehensive processing ability and consequent inclination to meticulously consider all relevant information and engage in piecemeal analysis when making financial decisions.

Hypothesis 16: *Gender* moderates the relationship between *Conscientiousness* and *Risk-Tolerance*.

As mentioned in the section relating *Agreeableness* to *Risk-Tolerance*, agreeable individuals act on less information when making financial decisions, i.e. they use information that is easily obtainable in the market and thus tend to engage in herd behaviour. In this research it is argued that this effect may be strengthened by the male tendency to selectively process the most available cues, giving little concern to subtle disconfirming information. They are more likely to invest in risky assets based solely on market trends and the possibility of high returns.

Hypothesis 17: *Gender* moderates the relationship between *Agreeableness* and *Risk-Tolerance*.

Neurotic individuals have an attentional bias towards threatening information, which leads to an overestimation and avoidance of risk. It is hypothesised that the lower female threshold for noticing and reacting to subtleties and disconfirming information (i.e. they notice and react to these subtleties quicker) may strengthen this effect. In contrast to this, being male may weaken this relationship, as they are less likely than their female counterparts to act on the slightest indication of risk.

Hypothesis 18: *Gender* moderates the relationship between *Neuroticism* and *Risk-Tolerance*.

Lastly, this research will argue for the inclusion of *Gender* as a moderator in the relationship between *Emotional Self-Management* and *Risk-Tolerance.* In a study using functional magnetic resonance imaging to create conditions of unregulated responding and cognitive regulation using validated negative stimuli, McRae, Oschner, Mauss, Gabrieli, and Gross (2008) found that both males and females may be equally effective at using cognitive reappraisal (*Emotional Self-Management*) to down-regulate negative affective responses (and so doing mitigate the anxiety provoking effects of financial decision-making under conditions of risk and uncertainty). They, however, found that whilst there is no difference in the frequency of its use, men display greater effort in employing the strategy to recontextualise negative stimuli into less emotional terms. According to these scholars men do so in a way that is quicker and more automatic. Thus, in terms of the definition of *Emotional Self-Management* provided in this research, which focuses on the relative frequency with which the strategies are displayed, it is argued that when two individuals, male and female, report using *Emotional Self-Management* at an equal rate, the effect of this variable on *Risk-Tolerance* may vary.

In addition, the *Selectivity Model* suggests the female tendency to comprehensively process information and give greater weight to disconfirming and subtle negative cues. Within the emotion regulation paradigm Thomsen, Mehlsen, Viidik, Sommerlund, and Zachariae (2005) posit that women are more likely to engage in maladaptive patterns of emotional regulation. One such maladaptive pattern is, for example, rumination, i.e. conscious, spontaneous, recurrent thoughts and/or images about past negative information. Rumination has a positive association with negative emotional experience such as anxiety and therefore, taken together, it is argued that the sensitivity to negative cues and the use of maladaptive patterns of emotion regulation would buffer, to some extent, the use of adaptive patterns, i.e. *Emotional Self-Management*. Therefore it is argued that under conditions of risk and uncertainty, women, firstly, being slower and less automatic and secondly, being cognitively focused on negative information, would experience more anxiety and discomfort under conditions of risk and uncertainty. Thus, it should once again be highlighted that both men and women may display equal frequencies and abilities to self-manage emotions; however, the slower female response to negative emotional experiences and use of maladaptive emotion regulation patterns may weaken the effect of *Emotional Self-Management* on *Risk-Tolerance*.

Hypothesis 19: *Gender* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*.

2.6.2 Age and Risk-Tolerance

Despite the vast amount of research conducted in order to determine the relationship between *Age* and *Risk-Tolerance*, there is a prevailing lack of consensus with regard to the strength and direction of this relationship. The argument for the inclusion of

Age as a moderating variable will be based on this lack of consensus. It will be argued in this research that given an equal standing on personality and emotion regulation variables, *Risk-Tolerance* will vary depending on an individual's *Age*. Thus, an individual's standing on the *Age* variable might either strengthen or weaken the relationship between personality and emotion regulation variables, and *Risk-Tolerance.* Subsequent arguments will be based on findings in literature that relate to the developmental tasks associated with different age groups.

A study by Baker and Haslem (1974) provided empirical evidence on the relationships of eight selected demographic/socioeconomic characteristics with the importance that investors assign to the risk and return characteristics of common stock, which includes five risk and return preference variables (expected dividend yield and expected price appreciation as measures of return; and market risk, marketability and price stability as measures or risk). *Age*, as one of the eight selected variables, was found to have a significant influence on three out of the five risk and return preference variables, where the general finding supported the notion that older persons are more risk averse, i.e. less risk-tolerant, than younger investors. Further to this, Lewellen et al. (1975) conducted a study on approximately 1 000 brokerage firm clientele and found an inverse *Age-Risk-Tolerance* relationship. Another study that considered the relationship between *Age* and *Risk*-Tolerance as well as specific personality characteristics (more specifically locus of control) and *Risk-Tolerance* was conducted by McInish (1982). The dependent variable was portfolio risk as measured by beta[16]. A random sample survey of 3 000 investors, in which 267 usable responses were obtained, provided support for a negative *Age-Risk-Tolerance* relationship. In a study by Hawley and Fujii (1994), data was drawn from the Survey of Consumer Finances (SCF)[17] out of a random sample of 3 824 households in the United States, where willingness to take financial risk was operationalised as the dependent variable, with a number of socio-demographic characteristics defined as independent variables. Results indicated that older

[16] Beta was defined in this study as an *ex post* risk measure. Beta is the coefficient of the return on market, in the regression of return on stock against return on market. Beta is calculated by: $R_{j,t} = \alpha_j + B_j R_{m,t} + \mu_t$ where $R_{j,t}$ is the price of stock j in period t, $R_{m,t}$ is the return on market in period t, α_j and B_j are parameters to be estimated, and μ_t is a random error term.

[17] The SCF is a widely used proxy, consisting of one item for financial *Risk-Tolerance* in the United States of America.

respondents are more risk averse, i.e. less risk-tolerant, than younger respondents and therefore also supported the negative *Age-Risk-Tolerance* relationship.

In more recent research the empirical results of the inverse relationship between *Age* and *Risk-Tolerance* have been further confirmed. For example, an extensive study by Yao et al. (2004) investigated changes in financial *Risk-Tolerance* levels over time. Financial *Risk-Tolerance* was operationalised as the dependent variable with demographic and socioeconomic characteristics (as well as attitudes) comprising the independent variables in the multivariate analysis. The study revealed that *Age* has a significant negative relationship with *Risk-Tolerance*.

However, despite the widespread support for an inverse relationship between *Age* and *Risk-Tolerance* as outlined above, several other research studies have produced some contradicting findings. Some studies support the aforementioned inverse relationship, whilst others argue for a positive or non-linear relationship between *Age* and *Risk-Tolerance*. For example, in an early study by Cohn et al. (1975) on 2 506 randomly selected accounts from a brokerage firm clientele, the regression results of the study indicated a positive correlation between *Age* and *Risk-Tolerance*. Grable and Lytton (1998) used *Age* as continuous variable and found support for the negative relation between self-perceived *Risk-Tolerance* and *Age*. Yao et al. (2005), using SCF datasets, examined the effect of race and ethnicity on subjective financial *Risk-Tolerance* (measuring *Age* as a continuous variable). These scholars found that, on average, each additional year increase in *Age* decreased the probability of taking some, high, or substantial risk by 2% (Yao et al., 2005). More recently, Van de Venter et al. (2012) conducted a longitudinal study of *Risk-Tolerance* and tested the common belief that financial *Risk-Tolerance* decreases with *Age*. Surprisingly, however, the study revealed a positive correlation coefficient between *Age* and *Risk-Tolerance*.

Others have proposed a non-linear relationship between *Age* and *Risk-Tolerance*. For example, Hallahan et al. (2003) and Hallahan et al. (2004) found that *Risk-Tolerance* increases up to a certain level, where after it will decline at an increasing rate. Therefore, proving significant non-linear effects in the relationship between *Age* and *Risk-Tolerance*. Hallahan et al. (2004) argued that as the baby boom cohort ages and moves into retirement, demand for more risky investment classes will shift to less risky classes, reflecting the decline in *Risk-Tolerance* as *Age* increases.

Similar to this finding, Corter and Chen (2006) conducted a study of *Risk-Tolerance*, measured with the Risk Tolerance Questionnaire (Grable & Lytton, 1999), on 63 graduate students in business at a major research university. They found support for the notion that the relationship between *Age* and *Risk-Tolerance* is not a simple linear one, but indeed non-linear. These findings were further replicated by Ameriks and Zeldes (2004), as well as Chambers and Schlagenhauf (2002).

The arguments for the inclusion of *Age* as a moderator within the *Client Risk-Tolerance* conceptual model will be based on the logic that as individuals enter the transition from adolescence to adulthood and from adulthood to old age, they experience increasing or changing responsibilities as they are confronted with the developmental tasks associated with each life stage. Many of these responsibilities are accompanied by an in increasing need for financial security and an active avoidance of financial strain which could change the way in which individuals respond to risk and uncertainty. Here, it is argued that the effect of certain personality variables on *Risk-Tolerance* will become more or less pronounced as individuals mature.

In line with the lifecycle hypothesis, it is argued in this research that a younger individual may have more time to recoup financial losses and replace leisure time with work in order to compensate for such losses. Thus, he/she is often more willing and able to make high-risk financial decisions. As the individual ages, however, this trend changes.

The developmental period between the ages of 15 and 30 is characterised by tremendous environmental changes. According to Roberts et al. (2001) it is the peak period for residential mobility, leaving school, marriage, fertility and employment. Demographers refer to this transition into adulthood as a period of demographic density with closely spaced life changes. Psychologists refer to it as a period characterised by identity commitment and (romantic) affiliation, where the individual is faced with the challenges of moving from dependence on family to increasing independence as a fully functioning member of society (Roberts et al., 2001).

As the individual moves through the different stages, he/she is likely to become future orientated as he/she starts planning for the developmental tasks associated with the next stage. The transition from adolescence to adulthood is likely to be accompanied by the need for financial steadfastness and self-sufficiency as the individual enters and advances into positions of maximum sex role specialisation, for e.g. parenthood, and other positions of power, responsibility and independence. The move from adulthood to old age is accompanied by an awareness of the fact that employment is likely to be terminated at some point in time. Thus, as the individual moves out of positions of power and decision-making, financial security and protecting accumulated wealth become important considerations in the individual's life. Thus, as an individual matures he/she may become increasingly prudent so as to protect hard earned wealth.

In light of the aforementioned it will be argued that an increase in *Age* will weaken the relationship between *Openness to Experience* and *Risk-Tolerance*. That is, when two individuals have the same standing on the latent variable *Openness to Experience,* the effect thereof on *Risk-Tolerance* will vary depending on their *Age*. Due to the tasks associated with aging, individuals are required to uphold a certain financial ideal which becomes more pressing as they move into different life roles as illustrated above. Thus, they become less concerned with financial experimentation and more concerned with upholding the status quo. This may buffer the effects of *Openness to Experience*, which serves as a natural inclination to engage in confident investment for the sake of doing so, on *Risk-Tolerance*. Similarly, it is expected that *Age* may buffer the effect of *Sensation Seeking* on *Risk-Tolerance*. Thus, even though two individuals with the same standing on *Sensation Seeking* derive pleasure and stimulation from risky financial decisions, the older one will be less inclined to engage in such decisions due to increasing financial conservatism and awareness of the consequences of risk.

Hypothesis 20: *Age* moderates the relationship between *Openness to Experience* and *Risk-Tolerance*.

Hypothesis 21: *Age* moderates the relationship between *Sensation Seeking* and *Risk-Tolerance*.

Moreover, given that older individuals become increasingly goal-directed and burdened with responsibility it would seem natural that the effects of *Conscientiousness* on *Risk-Tolerance* will be strengthened. As individuals move from adolescence into adulthood the role of socially prescribed normative tasks, such as partnership and parenthood, increase in importance and requires a sense of duty from individuals. This sense of duty does not go unaccompanied by its own financial consequences.

Hypothesis 22: *Age* moderates the relationship between *Conscientiousness* and *Risk-Tolerance*.

Lastly, it is expected that *Age* will strengthen the relationship between *Delay of Gratification* and *Risk-Tolerance.* Thus, it is argued that two investors who have the same ability to delay gratification will not necessarily have the same standing on *Risk-Tolerance,* if they are of different *Age*. Even though both investors are likely to cautiously gather and act on information, it is argued that the older individual could be more inclined to invest systematically and strategically in order to secure a certain financial reward in the future. In contrast to this, the younger investor may have enough leverage to accept higher risk investments with less certain returns as he/she has more time to recoup any financial losses. Thus, the point in time at which rewards are preferred will differ.

Hypothesis 23: *Age* moderates the relationship between *Delay of Gratification* and *Risk-Tolerance*.

2.6.3 Income and Risk-Tolerance

Cohn et al. (1975) conducted an analysis of 972 responses by randomly selected, geographically stratified, brokerage firm clients regarding investment decision processes, goals, asset holdings and market beliefs. Subsequently, Cohn et al. (1975) concluded that relative investor risk aversion decreases with wealth and

Income, i.e. *Risk-Tolerance* increases with wealth and *Income*. Hawley and Fujii (1994) also indicated that individual investors with higher *Income* display the tendency to incur greater financial risk. Similarly, Yao et al. (2004) found that *Income* level generally has a significant positive relationship with *Risk-Tolerance.*

Deaves et al. (as cited in Croy et al., 2010) found a positive relationship between *Income* and *Risk-Tolerance.* Ciccheti and Dubin (1994) indicated that relatively affluent persons, specifically those who are well educated, tend to be less risk averse. They found that an increase in *Income* leads to a systematic increase in *Risk-Tolerance.*

This is in contrast to the findings of Freidman and Savage (1948), that postulated that higher-*Income* individuals (more specifically men) are less risk-tolerant than their lower *Income* equals. Similarly, Gregory (as cited in Hawley & Fujii, 1994) also suggested that wealthier individuals will generally be less risk-tolerant. More recently, Strydom & Metherell (2012) argued that higher *Income* individuals become more prudent to avoid losing their accumulated hard earned wealth.

Lewellen et al. (1974), however, failed to find a pattern between *Income* level and attitude toward risk. Their research produced contradictory evidence that risk aversion diminishes with personal affluence as well as indications that upper-income individuals consider themselves as no more or less risk inclined than their lower-*Income* counterparts. According to Baker and Haslem (1974) family *Income* was related to the importance that investors ascribe to expected dividend yield. The findings, however, delivered inconsistent results. Less family *Income* was related to higher importance placed on dividend yield. However, the two lowest *Income* categories were related to no importance whilst maximum importance was related to both the lowest and highest *Income* categories. Strydom et al. (2009) also found that there was no significant relationship between *Income* and *Risk-Tolerance,* but also stated that the low response rate to their *Income* question made the reliability of their analysis questionable. Gumede (2009) also found that *Income* had a positive effect on *Risk-Tolerance*, but the relationship was not statistically significant.

Hallahan et al. (2003) and Hallahan et al. (2004) proceeded to establish that attitudes toward risk differs across *Income* levels. They found that individuals within higher *Income* brackets are better able to absorb risk, and are therefore more risk-tolerant. However, as *Income* further increased, they found a non-linearity in the *Income-Risk-Tolerance* relationship which was "consistent with the economic concept of diminishing marginal utility of money" – which states that the more money individuals have, the less they will value an additional dollar of *Income* (Hallahan et al., 2003, p. 490). The wealther individuals in society are more concerned with protecting their current wealth as opposed to increasing it.

For purposes of this research *Income* will be defined as the gross annual salary gained from participation in the labour market. In this research it will be argued that the more *Income* an individual has to his/her disposal, the more risk-tolerant he/she is likely to be, all things being equal. Financial stability (in terms of a larger *Income*) will provide the investor with greater financial leverage and thus, it is expected that an individual in the upper *Income* group will have greater access to financial resources which will allow him/her with the ability to allocate a greater proportion of such resources to risky financial decisions.

According to Strydom et al. (2009) an individual's level of financial security relates to the concept of *absolute risk aversion*. This can be defined as "the change in a nominal amount that is allocated to a risky asset as wealth increases" (Strydom et al., 2009, p. 2). It is argued that the nominal amount that is allocated to risky assets (or other investment decisions) will increase as *Income* increases.

All things being equal, it is expected that *Income* will moderate the relationship between the emotion regulation variables and *Risk-Tolerance*. Higher *Income* individuals, due to the higher nominal amount to their disposal, will have the objective ability to bear higher risk financial decisions. In addition to this, they are better able to absorb financial loss. In contrast to this, lower *Income* individuals are less able to absorb losses stemming from risky financial decisions. That is, an individual with a mediocre income is limited by a low objective ability to take risks, in spite of a greater willingness to do so.

However, as mentioned, empirical studies relating *Income* to *Risk-Tolerance* does not yield consistent results. Thus, as many scholars and practitioners have asserted (but neglected to empirically prove), it is argued that an individual's *Risk-Tolerance* level is primarily determined by his/her emotional make-up and ability to suppress or regulate affective responses evoked by decision-making under risk and uncertainty. However, this research will support the notion that this emotional willingness to take risks should be considered alongside one's financial capacity to bear risks, i.e. the financial ability to contribute additional financial capital should losses be sustained (which is often inevitable). Thus, *Income* may serve as a means to buffer against the possible negative effects of future uncertainties. According to Goel (2009) the attention of the financial advisor should be drawn firstly to the client's emotional willingness to take risk. That is, when the individual's willingness to take risks is greater or lower than his/her ability to bear risks, attention should be directed towards the danger that the client's willingness to assume risk may have in terms of jeopardising his/her ability to bear risks and achieve investment objectives. It is possible for an individual's financial capacity to take risk and emotional reactions towards risk to be incompatible or alike.

It is argued here that when two individuals with the same standing on the emotional regulation variables differ in terms of level of *Income*, their standing on the dependent variable *Risk-Tolerance* will vary to the extent that their *Income* levels vary. It is hypothesised that a higher *Income* level may afford the investor with the ability to contribute additional financial capital should losses in portfolio value be sustained. Knowing that additional financial capital is available may provide a level of cognitive and financial security that may serve to put the investor at ease, despite experiencing low levels of emotional comfort with a specific investment decision. Greater financial stability may serve to strengthen or buffer the effect of emotion regulation on *Client Risk-Tolerance* and thus play a part in predicting the individual's overall *Client Risk-Tolerance*.

Hypothesis 24: *Income* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*.

Hypothesis 25: *Income* moderates the relationship between *Emotional Self-Control* and *Risk-Tolerance*.

2.6.4 Education and Risk-Tolerance

According to Baker and Haslem (1974) (using data from a *Risk-Tolerance* questionnaire that was randomly distributed to 851 respondents in five brokerage firms) *Education* was related to price stability, where less educated individual investors placed higher importance on price stability, than investors with some college education. Furthermore, Hawley and Fujii (1994), in their analysis of SCF data, concluded that higher *Education* was related to higher *Risk-Tolerance.*

Recent research by Yao et al. (2004) revealed a significant positive relationship between *Education* and *Risk-Tolerance.* In tandem with this, Hallahan et al. (2003) in their exploratory investigation of the relation between *Risk-Tolerance* and demographic charactersitics, postulated that *Education* will increase an individual investor's ability to evaluate risks inherent to the investment process and therefore, endow them with a higher level of financial *Risk-Tolerance*. Based on this argument, Hallahan et al. (2004) reported that at least a trade/diploma level of *Education* was necessary for a significant increase in *Risk-Tolerance* to be perceived. Therefore, it could be concluded that a tertiary *Education* has a significant effect on *Risk-Tolerance.* Van de Venter et al. (2012) replicated this stance, theorising that a trade or tertiary diploma level of *Education* is needed for statistically significant increases in *Risk-Tolerance* scores to be observed, but suggested that *Risk-Tolerance* is a function of *Education* to a lesser degree than *Income* and wealth.

Haliassos and Bertaut (1995), and Zhong and Xiao (1995) found that individuals with a lower *Education* (more specifically without a college level *Education*) were significanly less likely to hold risky assets (stocks and bonds). More recently, Larkin, Lucey, and Mullholand (2013) also postulated that a higher educational level was associated with higher level of net assets.

Even though higher educational attainment has generally been accepted as a characteristic of high risk-tolerant individuals, there is reseach that suggests otherwise. For example, McInish (1982) reported a positive relationship between educational levels and *Risk-Tolerance*, however, the coefficients were not significant in any of the regressions. Similarly, Gumede (2009) failed to find a significant relationship between *Education* and *Risk-Tolerance*. More recently, in a study conducted on a diversified Pakistani sample of investors, bank managers and household individuals, Bashir, Uppal, Hanif, Yaseen and Saraj (2013) found that educational attainment did not have a significant influence on financial *Risk-Tolerance*.

In this research *Education* will be defined as the formal level of education completed by an individual. In line with the argument produced by Hallahan et al. (2004) it is hypothesised that higher educational attainment will increase an individual's ability to evaluate risks inherent to the investment process. Formal academic training may lead to a superior understanding and prudent assessment of risks and benefits. It is hypothesised that higher educational levels may lead to higher levels of financial literacy. Individuals with higher levels of *Education* will be more likely to make better predictions about future financial developments from past experience. In contrast to this, clients with lower academic qualifications may need more information when making investment decisions, and therefore financial advisors should be cognisant of the educational backgrounds of their clients when giving advice.

In this research it will be argued that educational attainment will moderate the relationship between emotion regulation variables and *Risk-Tolerance*. It is argued that a higher level of *Education* might serve as the catalyst for rational risk assessment, as opposed to emotionally laden decisions, during financial decision-making that is based on rational calculations, statistical predictions as well as past financial experience and knowledge to establish the probabilities of return. Once again, it is argued that two individuals with the same standing on emotion regulation variables will have differing, or the same levels of *Risk-Tolerance,* depending on their standing on the *Education* variable. Thus, even though an individual's emotional make-up predominantly influences his/her *Risk-Tolerance* levels, his/her ability to attain a rational grasp on the probabilities of risk and return, as a function of *Education*, may play a part in predicting his/her overall *Client Risk-Tolerance*.

Hypothesis 26: *Education* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*.

Hypothesis 27: *Education* moderates the relationship between *Emotional Self-Control* and *Risk-Tolerance*.

2.7 The Proposed Client Risk-Tolerance Conceptual Model

The proposed *Client Risk-Tolerance* conceptual model is depicted in figure 2.2. The initial aim of the study was to capture all of the hypothesised effects in a structural model and to test the fit of the structural model to a data set via SEM. However, it became apparent that it would not be possible to test the 12 hypothesised interaction effects[18] in this manner. Instead, the interaction effects represented by these variables had to be tested with a series of moderated multiple regression analyses, conducted via SPSS version 22.0 (IBM Corp, 2013). Consequently, statistical hypotheses according to the SEM convention could not formulated for the interaction hypotheses, and accordingly these variables could not be assigned the relevant SEM notation. Hence, these effects were included in the conceptual model depicted in figure 2.2, but could not be included in a structural model to be tested in SEM via LISREL 8.80 (Jöreskog & Sörbom, 2002). It was, however, still possible and necessary to test the remaining 15 hypotheses via SEM. Therefore, they were assigned the relevant notation and a reduced *Client Risk-Tolerance* structural model without the hypothesised interaction effects were constructed. The reduced structural model that was tested via SEM in LISREL is depicted in figure 2.3.

[18] LISREL conventions dictate that each latent variable should have at least two observed variables, in order to be included in a structural model. The nature of the demographic and socioeconomic variables did therefore not lend itself to being included in the LISREL structural model in this way. In addition, the number of cases in the dataset would not have been sufficient for the amount of parameters that would have been estimated, if the interaction effects were included in the model.

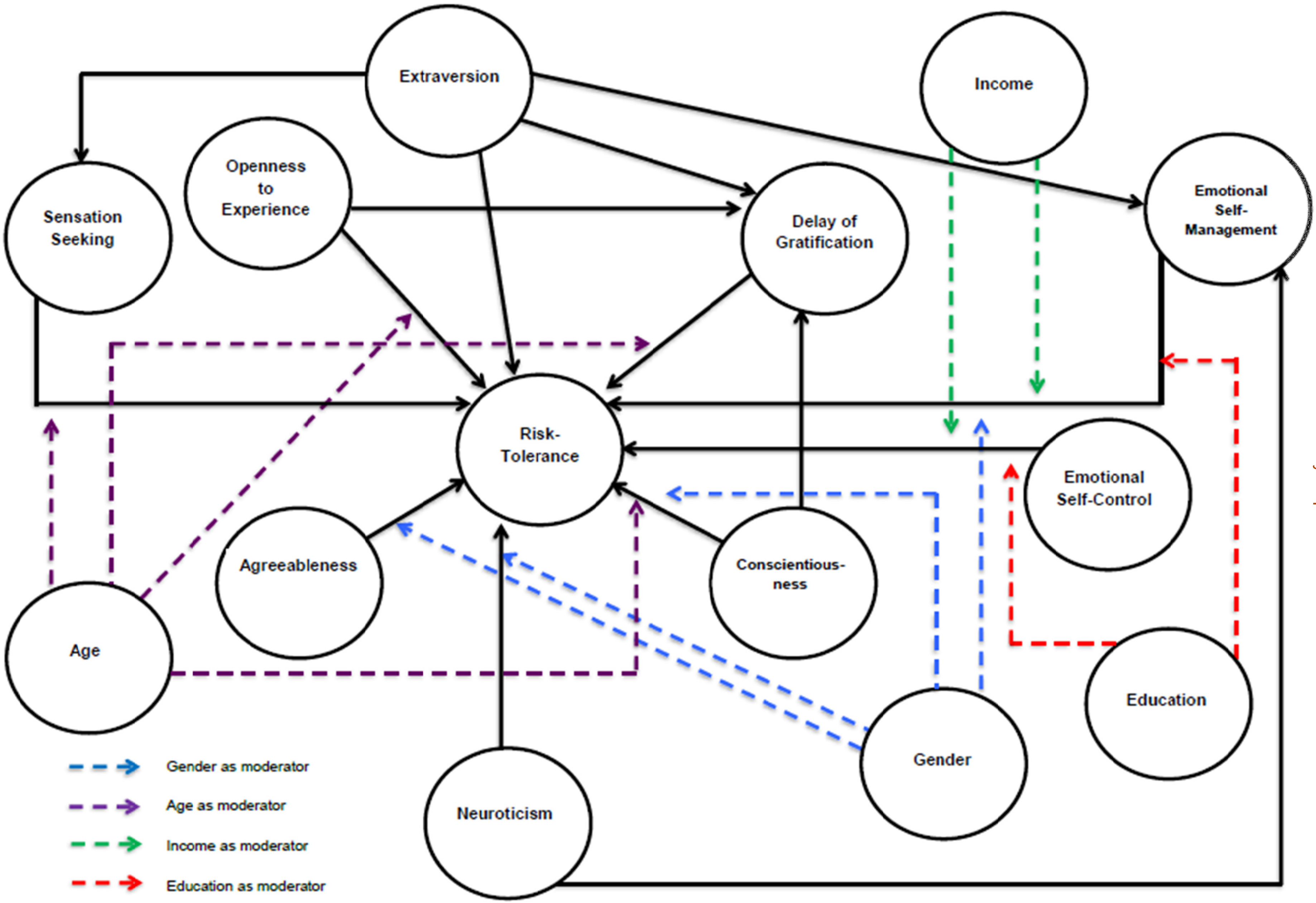

Figure 2.2. The Client Risk-Tolerance conceptual model

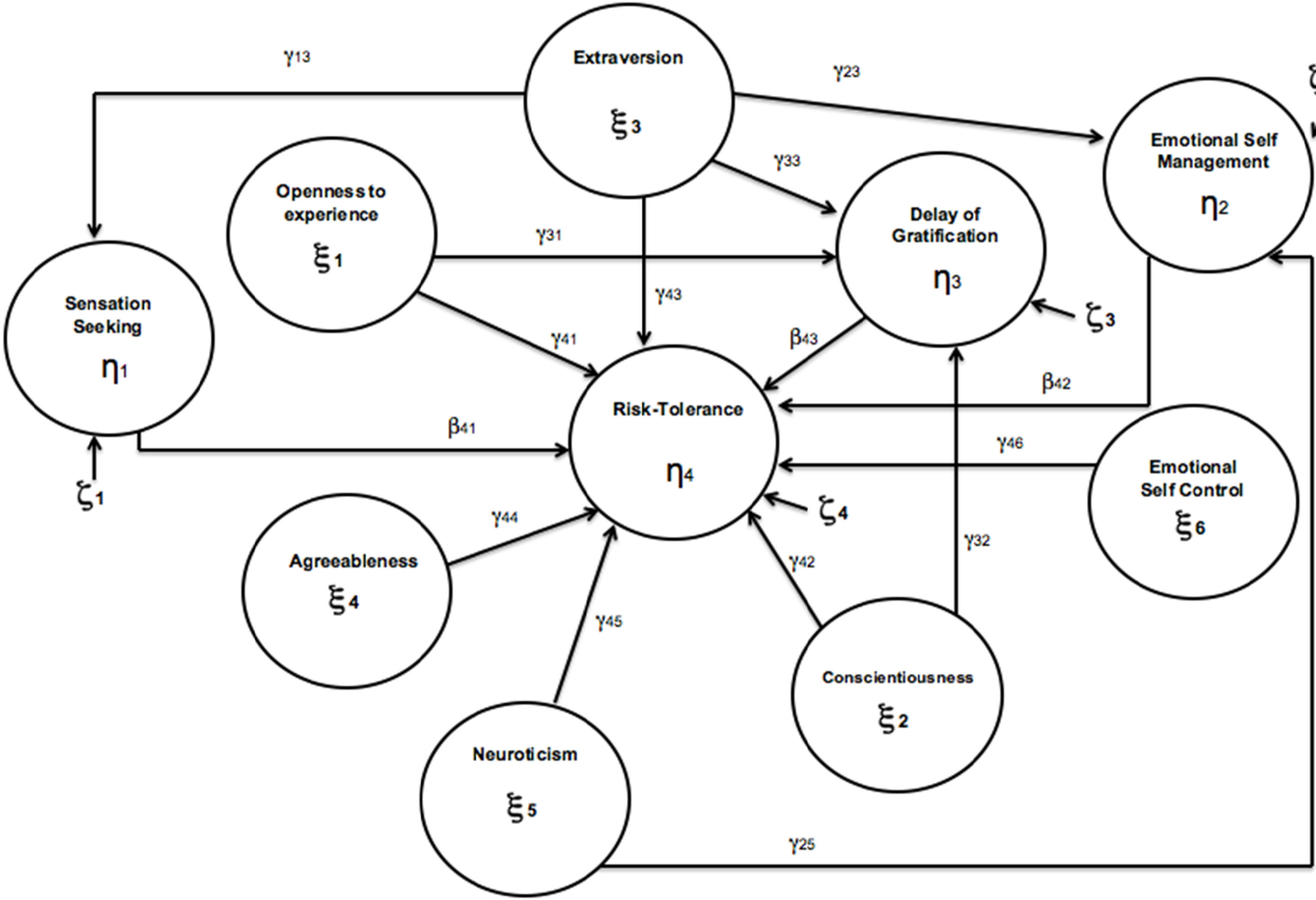

Figure 2.3. The hypothesised Client Risk-Tolerance reduced structural (LISREL) model

2.8 Conclusion

This chapter introduced a four-quadrant grid according to which clients can be classified in terms of their *objective risk-tolerance* and *subjective risk judgment* levels. This was accompanied by the actions that could be pursued by the financial advisor in relation to each of the four unique quadrants. A definition of the dependent variable *Client Risk-Tolerance* was provided, followed by a definition of the independent variable, *objective risk-tolerance*, as well as an overview of the literature devoted to the *objective risk-tolerance* variables, i.e. the various demographic and socioeconomic variables, as one set of predictors of *Client Risk-Tolerance*. A definition was constructed for *subjective risk judgment*, i.e. personality and emotional regulation, as an additional set of predictors.

Lastly, this chapter introduced the proposed *Client Risk-Tolerance* conceptual model. The identity of each of the proposed constructs comprising *objective risk-tolerance* and *subjective risk* judgment were established and individually defined and discussed in terms of the relevant literature in order to systematically uncover the logic underlying the model's structure. This included an explanation of the different relationships and interaction effects between the constructs together with the relevant hypotheses. The next chapter will present the methodology that was used to conduct the research and to investigate the stated hypotheses.

CHAPTER 3
RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

The literature study in chapter 2 presented a systematic and reasoned argument in response to the research initiating question formulated in chapter 1. Through comprehensive theorising, the resulting literature study culminated into an answer to the research initiation question in the form of a *Client Risk-Tolerance* conceptual model, presented in figure 2.2. A review of the relevant literature portrayed *Risk-Tolerance* as a complex function of a diverse range of personality and emotion regulation, as well as demographic and socioeconomic variables. Consequently, the *Client Risk-Tolerance* conceptual model was developed in an attempt to capture the complex interaction between the various factors that ultimately influence *Client/Investor Risk-Tolerance*.

The conceptual model is a schematic representation of the overarching substantive research hypothesis and the path-specific substantive research hypotheses that were constructed as a tentative answer to the research initiating question. The present study intended to empirically test the predictions made by the research hypotheses (schematically depicted in the explanatory conceptual model in figure 2.2). The *Client Risk-Tolerance* conceptual model can be considered valid or permissible to the extent that the reduced structural model (figure 2.3) fits the empirical data (analysis conducted with LISREL) and the multiple regression analysis (conducted to test the interaction effects captured in the conceptual model) yields satisfactory results. The validity and credibility of the implicit claim of this study to have come to the correct/true verdict with regard to the fit of the structural model and the multiple regression analysis results, is contingent upon the methodology used to arrive at such a verdict. The validity and credibility of the inferences made in the subsequent sections will ultimately be determined by the methods used to derive the conclusions. This is due to the fact that the research methodology is designed to serve the epistemic ideal of science (Theron, 2013).

The research methodology serves the epistemic ideal through two characteristics, i.e. objectivity and rationality. Objectivity is obtained through explicit and purposeful focus on the reduction of error. Rationality is obtained if science provides an opportunity for knowledgeable peers to critically appraise the validity of the research findings by assessing the methodological rigour of the processes used to arrive at the conclusions (Babbie & Mouton, 2001). If very little of the methodology used is made explicit, there is no way of evaluating the merits of the researcher's conclusions regarding the extent to which the structural model fits the empirical data. Therefore, the verdict simply has to be accepted at face value whilst in actual fact it might be inappropriate due to an inappropriate or incorrect procedure for investigating the merits of the structural model (Burger, 2011; Theron, 2013). The rationality of science thereby suffers, as does ultimately the epistemic ideal of science (Babbie & Mouton, 2001; Theron, 2013).

In light of the aforementioned, the aim of this chapter was inter alia to provide a detailed description of the methodological choices, and the arguments substantiating the various choices, in order to adhere to the principal of rationality. More specifically, this chapter comprehensively outlines a) the substantive research hypothesis; b) the research design; c) the statistical hypotheses; d) the sampling size and procedure; e) the measurement instruments used to operationalise the latent variables; f) the psychometric integrity of each instrument (i.e. reliability and validity); and g) the statistical techniques that were used to empirically evaluate the psychometric integrity of the measurement instruments, as well as the measurement and structural model.

3.2 Substantive Research Hypothesis

The research study aims to determine whether personality and emotion regulation variables (i.e. *subjective risk judgment*), as well as demographic and socioeconomic variables (i.e. *objective risk-tolerance*) of the individual can be used to differentiate amongst different levels of *Client Risk-Tolerance*. More specifically, the research study aims to determine the manner in which the various personality and emotion regulation latent variables are moderated by the demographic and socioeconomic latent variables to affect *Client-Risk Tolerance*. The theoretical argument presented in the literature study resulted in the inclusion of the following *subjective risk judgment* variables: *Extraversion, Conscientiousness, Openness to Experience, Agreeableness* and *Neuroticism, Sensation Seeking, Delay of Gratification,* *Emotional Self-Management* and *Emotional Self-Control*; as well as the *objective risk-tolerance* variables: *Gender, Age, Income and Education*. The resultant conceptual model is depicted in figure 2.2.

The overarching substantive research hypothesis (hypothesis 1) of this study is that the conceptual model depicted in figure 2.2 provides a valid account of the psychological processes underpinning the level of *Client Risk-Tolerance* during financial decision-making. The overarching substantive research hypothesis can be dissected into the following 27 more detailed substantive research hypotheses:

Hypothesis 2: Openness to Experience (ξ_1) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 3: Conscientiousness (ξ_2) has a negative linear effect on *Risk-Tolerance* (η_4)

Hypothesis 4: Extraversion (ξ_3) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 5: Extraversion (ξ_3) has a positive linear effect on *Sensation Seeking* (η_1)

Hypothesis 6: Agreeableness (ξ_4) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 7: Neuroticism (ξ_5) has a negative linear effect on *Risk-Tolerance* (η_4)

Hypothesis 8: Sensation Seeking (η_1) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 9: Delay of Gratification (η_3) has a negative linear effect on *Risk-Tolerance* (η_4)

Hypothesis 10: Extraversion (ξ_3) has a negative linear effect on *Delay of Gratification* (η_3)

Hypothesis 11: Openness to Experience (ξ_1) has a positive linear effect on *Delay of Gratification* (η_3)

Hypothesis 12: Conscientiousness (ξ_2) has a positive linear effect on *Delay of Gratification* (η_3)

Hypothesis 13: Emotional Self-Management (η_2) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 14: Emotional Self-Control (ξ_6) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 15: Extraversion (ξ_3) has a positive linear effect on *Emotional Self-Management* (η_2)

Hypothesis 16: Neuroticism (ξ_5) has a negative linear effect on *Emotional Self-Management* (η_2)

Due to the nature of the demographic and socioeconomic variables included in this study, i.e. *Gender, Age, Income* and *Education*, it was not possible to capture the hypothesised moderating effects within the *Client Risk-Tolerance* structural model[19]. Therefore, the interaction effects represented by these variables had to be tested with a series of moderated multiple regression analyses, conducted via SPSS version 22.0 (IBM Corp, 2013). Consequently, these effects were included in the overall conceptual model (but not the reduced structural model), and were not assigned the LISREL notation, as is the case in the abovementioned hypotheses. These hypotheses are:

Hypothesis 17: Gender moderates the relationship between *Conscientiousness* and *Risk-Tolerance*

Hypothesis 18: Gender moderates the relationship between *Agreeableness* and *Risk-Tolerance*

Hypothesis 19: Gender moderates the relationship between *Neuroticism* and *Risk-Tolerance*

Hypothesis 20: Gender moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

[19] LISREL conventions dictate that each latent variable should have at least two observed variables, in order to be included in a structural model. The nature of the demographic and socioeconomic variables did therefore not lend itself to being included in the LISREL structural model in this way.

Hypothesis 21: Age moderates the relationship between *Openness to Experience* and *Risk-Tolerance*

Hypothesis 22: Age moderates the relationship between *Sensation Seeking* and *Risk-Tolerance*

Hypothesis 23: Age moderates the relationship between *Conscientiousness* and *Risk-Tolerance*

Hypothesis 24: Age moderates the relationship between *Delay of Gratification* and *Risk-Tolerance*

Hypothesis 25: Income moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

Hypothesis 26: Income moderates the relationship between *Emotional Self-Control* and *Risk-Tolerance*

Hypothesis 27: Education moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

Hypothesis 28: Education moderates the relationship between *Emotional Self-Control* and *Risk-Tolerance*

3.3 Statistical Hypotheses for the Reduced Structural (LISREL) Model

The manner in which the statistical hypotheses are formulated depicts the logic underlying the proposed research design, as well as the nature of the statistical analyses. The proposed *Client Risk-Tolerance* reduced structural model consists of a number of endogenous and exogenous latent variables and causal paths are proposed between these variables. The notational system used in the formulation of the statistical hypotheses follows the structural equation modelling (SEM) convention associated with LISREL (Jöreskog & Sörbom, 1996b). In order to investigate the hypothesised model's fit, an exact fit and close fit null hypothesis were tested.

The overarching substantive research hypothesis (hypothesis 1) states that the structural model depicted in figure 2.3 provides a valid account of the psychological processes that underpin *Client Risk-Tolerance*. If the overarching substantive research hypothesis would be interpreted to mean that the structural model provides a perfect explanation for the psychological dynamics underlying *Client Risk-Tolerance*, the substantive research hypothesis translates into the following exact fit null hypothesis (hypothesis 2a[20]):

$$H_{02a}: \text{RMSEA} = 0$$
$$H_{a2a}: \text{RMSEA} > 0$$

However, the probability of obtaining an exact fit is doubtful. Consequently, the close fit null hypothesis should be considered as it takes the error of approximation into account. If the difference between the observed and reproduced score is equal to or less than 0.05, it implies close fit (Theron, 2013). If the overarching substantive research hypothesis would be interpreted to mean that the structural model provides an approximate explanation of the psychological dynamics underlying *Client Risk-Tolerance*, the substantive research hypothesis translates into the following close fit null hypothesis (hypothesis 2b):

$$H_{02b}: \text{RMSEA} \leq 0.05$$
$$H_{a2b}: \text{RMSEA} > 0.05$$

The overarching substantive research hypothesis was dissected into 27 more detailed path-specific research hypotheses. Of these hypotheses, 15 were included in the reduced structural model and therefore, 15 path coefficient statistical hypotheses could be formulated and tested via SEM. These hypotheses are summarised in table 3.1. The remaining 12 hypotheses could not be tested via SEM. Instead, multiple regression analyses were conducted which did not necessitate the formulation of statistical hypotheses according to the SEM convention.

[20] The overarching substantive research hypothesis can be dissected into exact and close fit null hypotheses for the measurement model (H01a and H01b) and the structural model (H02a and H02b). Due to the fact that the presentation of the measurement model results precedes that of the structural model, it was decided to assign the numbers accordingly and in that order.

Hypothesis 2: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Openness to Experience* (ξ_1) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{03}: \gamma_{41} = 0$$

$$H_{a3}: \gamma_{41} > 0$$

Hypothesis 3: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Conscientiousness* (ξ_2) has a negative linear effect on *Risk-Tolerance* (η_4)

$$H_{04}: \gamma_{42} = 0$$

$$H_{a4}: \gamma_{42} < 0$$

Hypothesis 4: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Extraversion* (ξ_3) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{05}: \gamma_{43} = 0$$

$$H_{a5}: \gamma_{43} > 0$$

Hypothesis 5: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Extraversion* (ξ_3) has a positive linear effect on *Sensation Seeking* (η_1)

$$H_{06}: \gamma_{13} = 0$$

$$H_{a6}: \gamma_{13} > 0$$

Hypothesis 6: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Agreeableness* (ξ_4) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{07}: \gamma_{44} = 0$$

$$H_{a7}: \gamma_{44} > 0$$

Hypothesis 7: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Neuroticism* (ξ_5) has a negative linear effect on *Risk-Tolerance* (η_4)

$$H_{08}: \gamma_{45} = 0$$

$$H_{a8}: \gamma_{45} < 0$$

Hypothesis 8: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Sensation Seeking* (η_1) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{09}: \beta_{41} = 0$$

$$H_{a9}: \beta_{41} > 0$$

Hypothesis 9: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Delay of Gratification* (η_3) has a negative linear effect on *Risk-Tolerance* (η_4)

$$H_{010}: \beta_{43} = 0$$

$$H_{a10}: \beta_{43} < 0$$

Hypothesis 10: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Extraversion* (ξ_3) has a negative linear effect on *Delay of Gratification* (η_3)

$$H_{011}: \gamma_{33} = 0$$

$$H_{a11}: \gamma_{33} < 0$$

Hypothesis 11: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Openness to Experience* (ξ_1) has a positive linear effect on *Delay of Gratification* (η_3)

$$H_{012}: \gamma_{31} = 0$$

$$H_{a12}: \gamma_{31} > 0$$

Hypothesis 12: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Conscientiousness* (ξ_2) has a positive linear effect on *Delay of Gratification* (η_3)

$$H_{013}: \gamma_{32} = 0$$

$$H_{a13}: \gamma_{32} > 0$$

Hypothesis 13: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Emotional Self-Management* (η_2) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{014}: \beta_{42} = 0$$

$$H_{a14}: \beta_{42} > 0$$

Hypothesis 14: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Emotional Self-Control* (ξ_6) has a positive linear effect on *Risk-Tolerance* (η_4)

$$H_{015}: \gamma_{46} = 0$$

$$H_{a15}: \gamma_{46} > 0$$

Hypothesis 15: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Extraversion* (ξ_3) has a positive linear effect on *Emotional Self-Management* (η_2)

$$H_{016}: \gamma_{23} = 0$$

$$H_{a16}: \gamma_{23} > 0$$

Hypothesis 16: In the proposed *Client Risk-Tolerance* structural model it was hypothesised that *Neuroticism* (ξ_5) has a negative linear effect on *Emotional Self-Management* (η_2)

$$H_{017}: \gamma_{25} = 0$$

$$H_{a17}: \gamma_{25} < 0$$

Table 3.1

Path coefficient statistical hypotheses

Hypothesis 2	Hypothesis 3	Hypothesis 4	Hypothesis 5
H03: $\gamma 41 = 0$	H04: $\gamma 42 = 0$	H05: $\gamma 43 = 0$	H06: $\gamma 13 = 0$
Ha3: $\gamma 41 > 0$	Ha4: $\gamma 42 < 0$	Ha5: $\gamma 43 > 0$	Ha6: $\gamma 13 > 0$
Hypothesis 6	Hypothesis 7	Hypothesis 8	Hypothesis 9
H07: $\gamma 44 = 0$	H08: $\gamma 45 = 0$	H09: $\beta 41 = 0$	H010: $\beta 43 = 0$
Ha7: $\gamma 44 > 0$	Ha8: $\gamma 45 < 0$	Ha9: $\beta 41 > 0$	Ha10: $\beta 43 < 0$
Hypothesis 10	Hypothesis 11	Hypothesis 12	Hypothesis 13
H011: $\gamma 33 = 0$	H012: $\gamma 31 = 0$	H013: $\gamma 32 = 0$	H014: $\beta 42 = 0$
Ha11: $\gamma 33 < 0$	Ha12: $\gamma 31 > 0$	Ha13: $\gamma 32 > 0$	Ha14: $\beta 42 > 0$
Hypothesis 14	Hypothesis 15	Hypothesis 16	
H015: γ□6 = 0	H016: $\gamma 23 = 0$	H017: $\gamma 25 = 0$	
Ha15: $\gamma 46 > 0$	Ha16: $\gamma 23 > 0$	Ha17: $\gamma 25 < 0$	

3.4. Research Design and Procedure

3.4.1 Research design

To empirically evaluate the merit of the overarching substantive research hypothesis, and thereby serve the epistemological ideal of science, requires a strategy that provides unambiguous empirical evidence (Theron, 2013). This strategy will be effected in the form of a research design which can be defined as the plan on how one intends to empirically test the overarching substantive research hypothesis (Babbie & Mouton, 2001; Kerlinger & Lee, 2000).

The ideal of the research design is to ensure empirical evidence that will allow for unambiguous interpretation for, or against, the stated hypotheses. This will ultimately be determined by the ability of the research design to control variance in the measurement of the exogenous latent variables. This, in turn, is a three-faceted concept (Theron, 2013). Ideally, one would want to maximise systematic variance, minimise error variance and control systematic non-relevant variance in order to increase the likelihood that H_{02b} will be rejected during statistical hypothesis testing (Kerlinger & Lee, 2000).

For purposes of this research, an *ex post facto* correlation design was used to test the overarching substantive research hypothesis. Correlation research examines the relationship of two or more variables that do not lend themselves to experimental manipulation and random assignment. Their manifestations have already occurred or they are not inherently manipulable (Theron, 2013) and therefore, the researcher does not have direct control over them (Kerlinger & Lee, 2000). The logic underlying the *ex post facto* correlation design involves that the researcher obtains measures on the observed variables and calculate the observed covariance matrix (Kerlinger & Lee, 2000). Estimates for the freed structural and measurement model parameters must be obtained in an iterative fashion with the objective of reproducing the observed covariance matrix as closely as possible (Diamantopoulos & Siguaw, 2000; Theron, 2013). If the fitted model fails to accurately reproduce the observed covariance matrix, the structural model does not provide an acceptable explanation for the observed covariance matrix and thus, the structural model depicted in figure 2.3 does not provide a satisfactory explanation of the psychological process underpinning *Client Risk-Tolerance*. The converse, however, is not true. If the covariance matrix derived from the estimated structural and measurement model parameters closely agree with the observed covariance matrix, it would not imply that the psychological dynamics postulated by the structural model necessarily produced the observed covariance matrix (Theron, 2013). A high degree of fit between the observed and estimated covariance matrices would only imply that the psychological processes portrayed in the structural model provide a single plausible explanation for the observed covariance matrix (Theron, 2013).

3.4.2 Research participants

The units of analysis for this study included individuals seeking, or already receiving, financial advice from various financial institutions in the Western Cape, South Africa. A detailed discussion on the nature of the research participants contained in the sample for this study will be provided at the beginning of chapter 4.

3.4.3 Sample and sample design

The aim of the research study was to determine whether personality and emotion regulation, as well as certain demographic (*Age* and *Gender*) and socioeconomic variables (*Education* and *Income*) of the individual could be used to differentiate among different levels of financial or *Client Risk-Tolerance*. Therefore, the unit of analysis in the study was the individual client or investor. This implied a relatively large target population. Due to the nature and magnitude of the target population, it was not feasible to obtain measurements from each individual client or investor in the target population (N). Instead, it was deemed more practical to obtain measurements from a representative sample (n) of the target population. That is, a subset of the target population that accurately reflects the properties of that population in as close a way as possible. This method requires the formation of a sampling population or a sampling frame, i.e. the final sampling units in the target population that have a non-zero probability of being selected. The ideal would be to minimise the gap between the sampling population or frame and the target population, so as to attain two coinciding populations. In this study, it was an unobtainable ideal to define a sampling population that largely overlapped with the target population. And thus, it was not possible to draw a representative sample from the target population. Due to the nature of the target population implied by this study, non-probability sampling, more specifically convenience sampling, was utilised. Individuals seeking or already receiving financial advice from various financial institutions qualified to be included in the sample. Any such individuals were suitable for inclusion as long as they indicated a willingness to participate in the study by signing the personal consent form (appendix C).

The extent to which the research results can be generalised from the sampling population to the target population depends not only on the representativeness of the chosen sample, but also on the number of participants in the sample.

The decision regarding the sample size of this research study was contingent on two considerations. Firstly, SEM requires a sufficiently large sample size in order to produce reliable estimates (Hair, Black, Babin, Anderson, & Tatham, 2006). Sample sizes of 200 observations or larger (but not exceeding 400) appears to be satisfactory for most SEM applications (Bagozzi & Yi, 2012; Hair et al. 2006; Kline, 2010). Hair et al. (2006) argue against the use of samples exceeding 400 participants, as the SEM analysis becomes too sensitive and susceptible to differences in the data, resulting in goodness-of-fit measures that show poor fit. Secondly, the practical and logistical considerations such as cost, availability and suitability of the respondents were taken into account when the decision regarding the sample size was made.

In light of the aforementioned considerations, a sample size of 200 was deemed optimal for this study to succeed. Each individual participant was required to sign the personal consent form and ethical clearance from *Stellenbosch University* was obtained.

3.4.4 Ethical considerations during data collection

The potential ethical risks associated with the proposed research were examined to ensure that the dignity, rights, safety and well-being of the research participants were protected and not compromised. Empirical behavioural research of this nature that requires the active involvement of individual research participants, i.e. individual investors or clients, could be detrimental to the dignity, rights, safety and well-being of such participants. Therefore, the critical question was whether this compromise could be justified by the purpose of this research. As argued throughout, the purpose of this research study was to arrive at conclusions that would assist in optimising the service delivery of the financial advisor by providing him/her with the means to better understand individual investors in order to provide advice that is tailored to the individual's willingness and ability to take risks, i.e. their *Risk-Tolerance* levels.

As outlined in the introduction to this research, interventions focusing on enhancing the ability of the financial advisor to deliver sound financial advice will contribute to an efficient financial services sector, which in turn, may have a beneficial impact on the greater economy and society. The critical question was whether the costs incurred by research participants would balance with the expected benefits of the research accrued to society[21].

The research participants were given the opportunity to voluntarily accept or decline the invitation to participate. In line with Annexure 12 of the *Ethical Rules of Conduct for Practitioners Registered under the Health Professions Act* (Act no. 56 of 1974), in order for research participants to make an informed decision, the psychologist had to ensure that individuals were informed about, and agreed with, the following aspects

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[21] Costs in this regard refer to sensitive data that was gathered, i.e. data pertaining specifically to the *Income* levels of individual participants.

of the research study: the objective and purpose of the research; what participation in the research entailed, i.e. the research procedures; the potential risks, discomforts and benefits associated with the research; how the research results were going to be disseminated and used; the identity of the researcher investigators and what their affiliation is; where additional inquiries about the research could be made; their rights as participants; and where additional information on their rights as research participants could be obtained. As part of the process of obtaining ethical clearance an informed consent template outlining the aforementioned issues was submitted to the Research Ethics Committee (REC) Human Research (Humanities) of Stellenbosch University. Ethical clearance was granted by the REC after inspection of all the documents, thereby concurring that all ethical issues had been sufficiently addressed by the researcher.

3.4.5 Data collection

Financial institutions are not permitted to provide client contact and personal details to outside parties. Thus, no individual email addresses were sought from any financial institution. Upon receipt of ethical clearance to conduct the research, informed institutional permission was obtained from the relevant financial institutions in order to gain access to their client base (see appendix A and appendix B). More specifically, access to the financial advisors and their clients were gained through a local networking organisation for independent financial planning professionals who work together to improve service delivery to employers, employees and individuals in the financial sector. Members of this association were invited to participate in the study by the head of the networking organisation. Other financial institutions, independent of this networking organisation were also approached to participate in the study. Participation in this study required of the financial advisors to identity clients willing to participate in the study. They were tasked with the process of distributing and collecting the questionnaires.

Two formats of the questionnaire were used. One group of advisors preferred the use of a hard copy questionnaire, which they personally distributed to their clients (see appendix D). The researcher collected this at a specified time, date and location of the advisor's choice, or alternatively the advisor scanned and attached all anonymously completed questionnaires in an email to the researcher. Some participants, however, were more comfortable with submitting the completed questionnaires directly to the researcher[22]. These questionnaires were stored anonymously, after which the e-mail was deleted immediately. In addition to this, the researcher presented her research study to a group of clients at a leading financial institution's quarterly seminar, where hard copy questionnaires were distributed to all individuals present. Another group of advisors preferred the use of the electronic version, created as a *pdf* form, which was distributed by means of an e-mail[23]. To some extent, the study relied on snowball sampling, where a group of participants forwarded the electronic questionnaires to other individuals who met the necessary inclusion criteria, i.e. individuals seeking or receiving financial advice from a financial institution. Snowball sampling is a non-probability sampling technique where existing research subjects recruit additional subjects among their acquaintances (Babbie & Mouton, 2002). This helped in the quest of ensuring that a large enough sample was obtained.

The data collected via the electronic and hard copy questionnaires were anonymous and treated as confidential. Confidentiality was maintained by restricting access to the data to the researchers by storing the data on a password-protected computer.

The informed consent formulation in appendix C outlined all the aforementioned ethical aspects to the research participant.

3.4.6 Data analysis

The data in this study was analysed using a range of quantitative techniques. This included the use of item analysis, exploratory factor analysis, confirmatory factor analysis, SEM, as well as multiple regression analyses. The subsequent section will present a detailed discussion on the various data analysis techniques that were employed to investigate the research hypotheses as well as certain aspects of the measurement instruments (e.g. factor structure and internal consistency).

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[22] Participants were informed that by e-mailing the questionnaire to the researcher, anonymity were forfeited. Those that did so, therefore, willingly forfeited their right of anonymity. All data collected in this study, however, remains confidential.

[23] These e-mails were forwarded by the financial advisor to their clients; therefore, the research did not obtain any client information (i.e. e-mail addresses) from the financial advisors.

3.4.6.1 Missing values

Before the data was analysed, the presence of missing values needed to be addressed. Missing values often arise due to non-response of participants, absenteeism etc. (Mels, 2003). The method through which the missing values were addressed depended on the number of missing values and the nature of the data, i.e. whether the indicator variables followed a multivariate normal distribution.

The following five options were considered for the treatment of missing values:

1. List-wise deletion
2. Pair-wise deletion
3. Imputation by matching
4. Multiple imputations
5. Full information maximum likelihood (FIML)

Once the data were collected and the nature and extent of the missing values were known, a decision with regard to the preceding approaches were made. In this study the missing values were treated by using imputation by matching. A thorough discussion and motivation of this process is presented in section 3.5.2.

3.4.6.2 Item analysis

The various scales used to operationalise the latent variables depicted in the reduced structural model in figure 2.3, were developed to measure a specific construct or dimension of a construct carrying a specific constitutive definition. Items have been developed to reflect an individual's standing on these specific latent variables. The items were designed to function as stimulus sets to which test takers respond with behaviour that is a reasonably uncontaminated expression of a specific underlying latent variable (Theron, 2013). The items comprising the various scales were designed to reflect clients' standing on the various uni-dimensional latent variables and therefore, their responses to the items of each scale should reflect a reasonable degree of consistency.

Item analysis was performed to (a) determine the reliability of the indicators of each latent variable, (b) evaluate the homogeneity of each sub-scale, and (c) screen items prior to their inclusion in the item parcels that represent each intended latent variable in the *Client Risk-Tolerance* reduced structural model (Van Heerden, 2013). The objective of the item analysis was to locate the items that did not successfully reflect the intended latent variable, and therefore, threatened the internal consistency of the scale in which it was included. Poor items fail to discriminate between different levels of the latent variable they were intended to reflect and/or will furthermore fail to reflect a common latent variable. The items that did not contribute to the internal consistency of the latent dimension in question were flagged and considered for elimination. From the results of the analyses, a number of item statistics were investigated to flag possible problematic items. The results of each instrument or subscale were analysed to reach a decision regarding the retention or deletion of items in the respective scales.

The basket of evidence that were used during this process included the following classical measurement theory item statistics: (a) the item-total correlation, (b) the squared multiple correlation, (c) the change in subscale reliability if the item were to be deleted, and (d) the inter-item correlations. SPSS version 22.0 (IBM Corp, 2013) was utilised to perform the item analyses.

3.4.6.3 Exploratory factor analysis

Exploratory factor analysis (EFA) is a statistical procedure used to uncover the underlying factor structure of a set of variables. The overarching goal of EFA is thus to allow the data to identify the interrelationships amongst a set of variables. In this study the use of EFA to inspect the factor structures of the instruments in question was contingent on the results of the confirmatory factor analysis (CFA). EFA was only performed if the CFA results suggested a poor fit between the observed data and the original theoretical model. Consequently, EFA was only performed on the *Emotional Self-Control* scale of the Genos Emotional Intelligence Inventory (Gignac, 2010). The objective of this analysis was to inspect the factor structure of the scale in more detail.

The architecture of the scales used to operationalise the latent variables comprising the reduced structural model reflects the intention to construct essentially one-dimensional sets of items. The items comprising the various scales/subscales were designed to operate as stimulus sets to which test respondents will react with behaviour that is primarily a manifestation of a specific uni-dimensional latent personality or emotion regulation variable (Van Heerden, 2013). The reaction to each item is, however, never solely dependent on the latent dimension they were tasked to reflect, but also on a number of other systematic, non-relevant latent variables and random error influences (Guion, 1998). The systematic error does, however, not correlate across items of a scale/subscale. Therefore, the assumption is that only the relevant latent variable is a common source of variance across items in a scale. This implies that if the latent variable of interest would be statistically controlled, the partial correlation between items would approach zero (Hulin, Drasgow, & Parsons, 1983), proving the existence of a single underlying factor. The design intention is always to obtain items that load relatively strongly on the specific underlying latent variable.

Principal axis factor (PAF) analysis, as well as principal component factor analysis (PCA) was used as extraction techniques. The decision on the number of factors to extract was based on the Eigen-value-bigger-than-one rule, as well as the scree plot. The loading of items on factors was considered satisfactory if $\lambda_{ij} > 0.40$ (Brown, 2015). SPSS version 22.0 (IBM Corp, 2013) was used to perform the dimensionality analyses.

3.4.6.4 Confirmatory factor analysis

As part of the process to evaluate the psychometric quality of the various measurement instruments, confirmatory factor analysis (CFA) was conducted as a means of testing how well the measured indicator variables represent a smaller number of latent constructs (Hair et al., 2006).

Despite being similar in many respects, Hair et al. (2006) argue that CFA and EFA are philosophically quite different. CFA requires of the researcher to specify the number of factors that exist within a set of variables, as well as the relationships between the observed variables and unobserved factors, before results can be computed. CFA requires a robust empirical and conceptual foundation and is typically conducted after the underlying structure has been tentatively established by prior empirical analyses using EFA, as well as on theoretical grounds (Brown, 2015).

As such, the CFA serves to corroborate the observed structures of the constructs. In the present research study all CFAs were specified to test the original theoretical structure of the measurement instruments. SEM was used to test how well a priori pattern of factor loadings fits the actual data. Through CFA the researcher was able to accept or reject her predefined measurement theory of the constructs included in the study. The researcher can only continue to evaluate the research questions, once the factor structures of all the respective measurement instruments, are accepted with confidence (Boers, 2014). LISREL 8.8 (Du Toit & Du Toit, 2001) was used to perform the confirmatory factor analyses.

Variable Type

Before CFA can be performed the variable type must be specified and the normality of the data should be investigated. The responses to the items on all the instruments utilised in the research study were captured on ordinal scales. According to Jöreskog (2005) the ordinal nature of data requires the analysis of polychoric correlations and the asymptotic covariance matrix. However, results from a simulation study by Muthén and Kaplan (1985) revealed that the use of Maximum Likelihood (ML) estimation is permissible, where scales of five or more scale points are classified as continuous, and where these variables are relatively skewed and kurtotic. These scholars found that the standard error and chi-square estimates were not critically misrepresented when this method was applied. For their study, different estimation techniques (i.e. ML, Generalised Least-square, Asymptotically Distribution Free, and Categorical variable methodology) were applied within a CFA SEM framework on non-normal categorical variables, which were dealt with as interval scale (continuous) non-normal variables.

Therefore, for the purpose of this study, the items (i.e. observed variables) for all the questionnaires with five scale points were specified to be continuous in all of the CFA analyses. However, due to the varying nature of the scale points in the Risk Tolerance Questionnaire (RTQ) (Grable & Lytton, 1999), ranging from two to four response categories (and thus less than the required five points as proposed by Muthén and Kaplan, 1985), these variables were specified as ordinal. This implied that the process as proposed by Jöreskog (2005) above had to be followed.

Normality and estimation technique

The maximum likelihood estimation technique that LISREL uses by default to obtain estimates for the freed model parameters, assumes that the indicator variables follow a multivariate normal distribution. The null hypothesis that this assumption is satisfied was routinely tested in PRELIS for all of the measurement instruments in this research, to further ensure that SEM statistical assumptions were not violated (Jöreskog & Sörbom, 1996a). The results of the normality analyses are reported at the start of each CFA section for every separate measurement instrument, as well the final measurement model for the structural model, tested in this research. In cases where the null hypothesis of multivariate normality was rejected, Robust Maximum Likelihood (RML) was specified as the estimation technique (Tabachnick & Fidell, 2001). In cases where the null hypothesis of multivariate normality could not be rejected, Maximum Likelihood estimation would be utilised[24].

Goodness-of-fit indices

Goodness-of-fit indices provide a numerical summary of the discrepancy between the observed variables and the values expected under the statistical model in question. Thus, the goodness-of–fit of a model describes how well it accounts for a set of observations or data.

Model fit can be evaluated by inspecting a wide range of goodness-of-fit indices provided by LISREL. However, Diamantopoulos and Siguaw (2000) argue that none of the indices are unequivocally superior to the rest under all conditions, and that specific indices operate fairly differently under a range of conditions. Sample size, estimation procedure, model complexity, degree of multivariate normality and variable independence, or any combination thereof, may influence the statistical power of the resultant indices (Diamantopoulos & Siguaw, 2000).

A number of goodness-of-fit statistics was used to determine the validity of the measurement models in the current research study. These include the Satorra-Bentler chi-square (S-B χ 2), standardised root mean square residual (SRMR), root mean square error of approximation (RMSEA), non-normed fit index (NNFI), the

[24] ML estimation was never employed as the null hypothesis for the multivariate normality of all the instruments were always rejected, requiring RML estimation to be used.

comparative fit index (CFI) and the P-Value for Test of Close Fit. The selection of these indices was based on the fact that they are widely reported in other studies (Byrne, 1998; Hair et al., 2006). Simulation research by Hair et al. (2006) suggest that appropriate cut-off values for the aforementioned goodness-of-fit indices for good model fit, should be set by model characteristics such as sample size and the number of observed variables in the model. For a sample smaller than 250 participants (as is the case in the current research study with n = 205) the fit indices in table 3.2 are applicable (Hair et al., 2006) and will be referred to throughout this chapter.

Table 3.2

Suggested cut-off values of fit indices demonstrating Goodness-of-Fit given differential model complexity

	N<250		
GOF statistics	**m ≤ 12**	**12 < m < 30**	**m ≥ 30**
CFI/ NNFI	> .97	> .95	> .92
SRMR	Could be biased upward, use other indices	≤ .08	< .09
RMSEA	< .08	< .08	< .08
Models	BSSS DGI	Mini-IPIP Genos EI RTQ	Measurement model Structural Model

Note: GOF = goodness-of-fit; m = number of observed variables; N applies to number of observations per group when applying CFA to multiple groups at the same time; CFI = comparative fit index (CFI); NNFI = non-normed fit index; BSSS = Brief Sensation Seeking Questionnaire; DGI = Delaying Gratification Questionnaire; Mini-IPIP = Mini International Personality Item Pool; Genos EI = Genos Emotional Intelligence Inventory; RTQ = Risk Tolerance Questionnaire; Measurement model = Measurement model of the Client Risk-Tolerance Model; Structural Model = Client Risk-Tolerance Structural Model; Models = models in this study that comply with the different criterion.

(Hair et al., 2006)

a) Satorra – Bentler scaled chi square

Satorra and Bentler (2001) developed the S-B chi-square statistic (S-B $\chi 2$), which incorporates a scaling correction aimed at improving the chi-square approximation of goodness-of-fit test statistics in small samples, large models and in data where the distributional assumptions of normality are violated. The Satorra-Bentler scaled chi-square is generated when robust estimation techniques are employed. As mentioned, robust estimation techniques are used when data deviates from the normal distribution. Data that departs significantly from multivariate normality requires calculation of the Satorra-Bentler scaled chi square statistic (S-B χ 2) in order to provide an improved estimate of the fit of a model (Satorra & Bentler, 2001).

b) Standardised root mean residual

The standardised root mean residual (SRMR) is the standardised square root of the mean of the squared residuals. It is a measure of the mean absolute value of the residuals between individual observed and estimated covariance and variance terms. Because the SRMR is an absolute measure of fit, perfect model fit is indicated by SRMR = 0. Smaller values represent a better fit. Increasingly higher values represent worse fit. In research with a sample size of less than 250 respondents (as is the case in this research study), and with the number of observed variables ranging between 12 and 30 (which applies to certain measurement models tested in this study), a cut-off value of < .08 is generally considered to indicate good model fit (Hair et al., 2006).

c) The root mean square error of approximation

The root mean square error of approximation (RMSEA) avoids issues relating to sample size by analysing the difference between the model, with optimally chosen parameter estimates, and the population covariance matrix (Hooper, Coughlan, & Mullen, 2008). The value of 0 indicates the best fit, with increasingly higher values indicating worse fit. In general, values below .08 for the RMSEA are indicative of acceptable fit, with values below .05 suggesting a very good fit (Hair et al., 2006).

d) Comparative fit index and non-normed fit index

The closer the comparative fit index (CFI) and non-normed fit index (NNFI) values are to unity (1.00); the better the fit of the model in question. However, as a general guideline for the interpretation of the CFI and NNFI, Hair et al. (2006) recommend that values of .92 or higher provide a strong suggestion of a well-fitting model for a sample with less than 250 observations, and more than 30 observed variables. This cut-off value for good fit may, however, change if less observed variables are present in the specified model as illustrated in table 3.2.

3.5 Measurement Instruments

To evaluate the fit of the *Client Risk-Tolerance* structural model, the latent variables comprising the structural model had to be operationalised. Measures of the various exogenous and endogenous latent variables comprising the model were identified in order to obtain empirical evidence that the relationships hypothesised by the proposed *Client Risk-Tolerance* structural model offered a plausible explanation for differences observed in *Client Risk-Tolerance*. An evaluation of the relationships presented in the structural model would be problematic if the quality of the measurement instruments used to measure the latent variables were called into question (Diamantopoulos & Siguaw, 2000).

The existing research evidence needed to determine and support the psychometric integrity of the indicator variables, which were used to operationalise the latent variables of the proposed *Client Risk-Tolerance* structural model, is presented in the subsequent sections. Current available evidence supporting the validity and reliability of the respective instruments are included. Furthermore, the successes with which the indicator variables represent the latent variables comprising the structural model in this specific research study were empirically evaluated via item analysis, CFA and where necessary, EFA.

Item analyses were performed to determine whether the items belonging to a specific measure reflected a common underlying variable and whether all items of the respective measures sensitively discriminated between different states of the latent variable being measured. Poor items were flagged and considered for deletion. EFA was performed to determine whether the factor structure of a scale could be replicated. However, this analysis was performed only where the CFA results for a model suggested poor fit between the observed data and the original theoretical model.

This section will start with a discussion of the way in which the data was prepared after being captured in SPSS and the treatment of the missing values in the initial data set, after which each measurement instrument will be introduced. The presentation of each instrument will be structured around (a) a discussion of the existing validity and reliability research relating to each measurement instrument; (b) the extent to which the data satisfied the statistical assumptions relevant to the data analysis techniques; and (c) a discussion of the item analysis, CFA and where necessary, EFA conducted on each respective instrument and/or its subscales. All this information was used in determining the psychometric integrity of the indicator variables that were designed to represent the various latent variables contained in the proposed model.

3.5.1 Data preparation

All responses were captured in a comprehensive excel spreadsheet before being imported into SPSS. Accuracy of the dataset was ensured by cross-checking a random sample of ten percent (± 21) of original questionnaires with the captured data. There were various negatively coded items across the instruments used in the questionnaire. These items were recoded.

3.5.2 Missing values

Before the data was analysed, the presence of missing values needed to be addressed. Missing values occurred due to some random non-responses of participants to the hardcopy questionnaire. The method through which the missing values were addressed depended on a careful inspection of the data, i.e. the number of missing values and whether the data followed a multivariate normal distribution. In the current study the missing values issue were treated by using imputation by matching. Whilst it is acknowledged that methods like FIML and Multiple Imputation have clear advantages over the traditional methods of treating missing values (i.e. List-wise Deletion and Pair-wise Deletion), it should be noted that these methods require data that follows a multivariate normal distribution. The latter method also assumes that the responses of the participants are measured on a Likert Scale with five or more points (Prinsloo, 2013). For reasons relating to the varying nature of the scale points in the RTQ (Grable & Lytton, 1999), ranging from two to four response categories (and thus less than the required five points as proposed by Muthén and Kaplan, 1985), it was necessary to use the less stringent method of imputation by matching. Moreover, due to the a priori assumption that the intervals between adjacent categories in ordinal variables are arbitrary and thus, data does not follow a multivariate normal distribution, it was not possible to utilise the other methods (i.e. FIML and Multiple Imputation) for the RTQ data[25].

A few missing values occurred on the items comprising the comprehensive *Client Risk-Tolerance* Questionnaire. Each questionnaire consisted of 72[26] items. The sample consisted of 205 individuals. Consequently, the final data set consisted of 14 760 potential item responses. Of these 14 760 potential item responses, a total of 18 values were missing from the final data set. The 18 missing values comprised only .08% of the potential data set. The output further revealed that the total effective sample size under list-wise deletion would be 194. The distribution of missing values across the different measurement scales is described in table 3.3 and the distribution of missing values across the items of the *Client Risk-Tolerance* Questionnaire is indicated in table 3.4.

Table 3.3

Distribution of missing values across measurement model scales and demographic/ socioeconomic variables

INSTRUMENTS	NUMBER OF MISSING VALUES
Mini-IPIP (20 item scale)	5
Brief Sensation Seeking Scale (8 item scale)	0
Emotional Self-Management (10 item subscale)	2
Emotional Self-Control (10 item subscale)	0
Delaying Gratification Inventory Money Subscale (7 item subscale)	3
Risk Tolerance Questionnaire (13 item scale)	3
Gender	2
Age	2
Education	0
Income	1

[25] As the whole dataset had to be imputed in one analysis, imputation by matching had to be used, given the restrictions imposed by the RTQ data, even though FIML or Multiple Imputation may have been stronger techniques to use for the data from the other measurements.

[26] The 72 items consisted of the different items for each scale/subscale added to the four questions relating to demographic and socioeconomic factors. The calculation was as follows: Number of items per individual = 10 + 8 + 10 + 10 + 7 + 13 + 4 = 72.

Table 3.4

Distribution of missing values across measurement model items

IPIP01	*IPIP02*	*IPIP03*	*IPIP04*	*IPIP05*	*IPIP06*	*IPIP07*	*IPIP08*
0	0	0	0	0	0	0	0
IPIP09	*IPIP10*	*IPIP11*	*IPIP12*	*IPIP13*	*IPIP14*	*IPIP15*	*IPIP16*
1	1	0	0	1	0	0	0
IPIP17	*IPIP18*	*IPIP19*	*IPIP20*	*BSS01*	*BSS02*	*BSS03*	*BSS04*
0	0	1	1	0	0	0	0
BSS05	*BSS06*	*BSS07*	*BSS08*	*ER01*	*ER02*	*ER03*	*ER04*
0	0	0	0	0	0	0	0
ER05	*ER06*	*ER07*	*ER08*	*ER09*	*ER10*	*ER11*	*ER12*
0	0	0	0	0	0	0	0
ER13	*ER14*	*ER15*	*ER16*	*ER17*	*ER18*	*ER19*	*ER20*
0	0	0	0	2	0	0	0
DGI01	*DGI02*	*DGI03*	*DGI04*	*DGI05*	*DGI06*	*DGI07*	*RT01*
2	0	0	0	0	0	1	0
RT02	*RT03*	*RT04*	*RT05*	*RT06*	*RT07*	*RT08*	*RT09*
0	0	0	0	1	0	1	0
RT10	*RT11*	*RT12*	*RT13*				
1	0	0	0				

Imputation by matching assumes that the data values are missing at random. The basic idea underlying matching imputation is to impute each missing value with the observed score from another individual or "donor" case (Enders & Bandalos, 2001) that follows the same or a similar response pattern across a set of user-defined matching variables (Jöreskog & Sörbom, 1996b). A minimization criterion is used to identify a single individual that closely resembles the case with missing data. The primary limitation of this procedure is that imputation will refrain from occurring if no observation exists that has complete data on the set of matching variables (Enders & Bandalos, 2001). The cases with missing values after imputation are deleted by default, which poses a challenge for small sample sizes. This, however, did not present a problem in the current research and thus, it was considered as the best method to solve the missing values problem. Consequently, imputation by matching was used to impute the 18 missing values. All 205 cases were retained in the imputed sample.

3.5.3 The Big Five personality traits

The Mini-IPIP was developed by Donnellan, Oswald, Baird, and Lucas (2006). It is a brief measure of 20 items that encompasses the Big Five personality factors. It is a shortened version of the 50-item IPIP Five-Factor Model (IPIP-FFM) and contains four items per Big Five trait, i.e. *Extraversion, Conscientiousness, Openness to Experience, Agreeableness* and *Neuroticism*.

The Mini-IPIP was validated across a series of five studies by Donnellan et al. (2006) and produced respectable internal consistencies, with α equal to, or above .60. Furthermore, it tapped nearly the same Big Five content as the parent scale and the four-item scales were not remarkably deficient in comparison. Patterns of discriminant and convergent validity as well as test-retest correlations over several weeks and months offer similar results to that of the IPIP-FFM (Donnellan et al., 2006).

In light of the reduced length, the Mini-IPIP produced acceptable reliability coefficients, ranging from .65 for *Intellect/Imagination* (*Openness to Experience*) to .77 for *Extraversion* (Donellan et al., 2006). Convergent correlations between the Mini-IPIP and the 10-item IPIP-FFM scales ranged from .85 for *Intellect/Imagination* to .93 for *Extraversion* (Donnellan et al., 2006). The scale intercorrelations for the Mini-IPIP were successfully reduced, producing average absolute scale intercorrelations of r = .13 compared to r = .20 for the IPIP-FFM. The Mini-IPIP scales also produced a comparable pattern of convergent, discriminant and criterion-related validity with other Big Five measures (Botes, 2012). A series of regression analysis were conducted to evaluate and compare the predictive validity between the Mini-IPIP and other Big Five measures (BFI, IPIP-FFM). The multiple R-values were very similar across the three Big Five measures (Donnellan et al., 2006). Compared to BAS as the criterion measure, the values were R = .55 for the BFI, R = .60 for the IPIP-FFM and R = .54 for the Mini-IPIP (Donnellan et al., 2006).

A study by Cooper, Smillie, and Corr (2010) further examined the psychometric properties of the Mini-IPIP through CFA. The clearly interpretable factor structure and reliability estimates produced by Cooper et al. (2010) prove similar to that of Donnellan et al. (2006); therefore, lending additional support for the use of the Mini-IPIP as a practical and psychometrically sound shorter measure of the five factor model. It is reasonable to conclude that the Mini-IPIP offers a useful, efficient and economical means of measuring the Big Five traits especially in time-critical assessment conditions (Cooper et al., 2010; Donnellan et al., 2006) where it is expected of participants to complete a considerable number of items, as in the current study.

Participants were expected to rate how well each of the items (in sentence fragment form) describe them, using a five-point Likert scale ranging from “very inaccurate” to “very accurate”.

3.5.3.1 Descriptive statistics and item analyses

Item analyses were conducted on the data via the scales reliability procedure of SPSS version 22.0 (IBM Corp, 2013). The results of the analyses and descriptive statistics of the five scales comprising the Mini-IPIP, i.e. *Extraversion, Agreeableness, Neuroticism, Conscientiousness* and *Intellect/Imagination (Openness to Experience),* are presented in table 3.5.

The *Extraversion* subscale produced an acceptable reliability coefficient (.729). Although slightly below the accepted .70 cut-off[27] the reliability coefficients obtained for the *Agreeableness* (.689) and *Intellect/Imagination* (.650) scales were still considered reasonable. It is, however, widely acknowledged that personality measures generally tend to produce lower coefficient alphas (Hale & Astolfi, 2014). The coefficient alphas of the remaining two scales were somewhat concerning as the

[27] Setting a definitive cut-off value for the evaluation of test/scale adequacy and reliability, is at best debatable and contentious (Prinsloo, 2011). The uncritical use of alpha can lead to situations in which a test or scale is falsely discarded or criticised for not generating trustworthy results (Tavakol & Dennick, 2011). Therefore, one has to consider the impact of various contextual factors like scale length, sample homogeneity, and the purpose of the assessment. Despite these reservations, the internal consistency/reliability of each measured scale/subscale was considered acceptable if the Cronbach’s alpha value exceeded .70.

obtained values did not meet the criteria set for this study, .548 (*Neuroticism*) and .588 (*Conscientiousness*).

The value of Cronbach's alpha (0 to 1) is a function of the number of items and the correlation between the items. Given a scale of a certain length, the higher the common variance of the items comprising the scale, the higher the coefficient alpha is likely to be (Roszkowsi & Soven, 2010). Thus, the coefficient of internal consistency is attenuated by a limited number of scale items. It could, therefore, be argued that the lower coefficient alphas obtained in this instance could be a reflection of the fact that the subscales consisted of a limited number of subscale items (m = 4). It should also be noted that these results were consistent with the modest results (ranging from .65 to .77) obtained in the original validation study by Donnelan et al. (2006). Thus, in general, it would seem that the scale produces lower alpha values and therefore, for the purposes of this research, the Cronbach's alphas were deemed acceptable.

Table 3.5

The means, standard deviation and reliability statistics for the Mini-IPIP subscales

MINI-IPIP subscale	Number of items	M	SD	A
Extraversion	4	13.39	3.221	.729
Agreeableness	4	15.30	2.689	.689
Neuroticism	4	10.55	2.758	.548
Conscientiousness	4	15.34	2.785	.588
Intellect/Imagination[28]	4	14.23	2.842	.650

The low Cronbach's alphas obtained for the majority of the subscales pointed towards the fact that the items do not seem to respond in unison to the systematic differences in the respective latent variables. Consequently, the item statistics of the subscales were inspected. All item statistics displayed somewhat incoherent sets of items.

The inter-item correlation matrix of the *Extraversion* subscale revealed modest correlations (.319 to .506) with low squared multiple correlations ranging from .221 to

[28] Intellect/Imagination refers to the Big Five personality trait of Openness to Experience.

.377. However, none of the items on this subscale, if deleted, would have resulted in a significant increase in the current Cronbach's alpha of .729. Similarly modest inter-item correlations were observed for the *Agreeableness* subscale (ranging from .245 to .542), with squared multiple correlations ranging from .247 to .404. Once again, none of the items, if removed, would have incurred an increase in the current Cronbach's alpha of .689 for this subscale. The *Openness to Experience* subscale (referred to as *Intellect/Imagination* in the measurement instrument) obtained inter-item correlations ranging from .154 to .481, squared multiple correlations of .226 to .286, and no substantial increase in the subscale Cronbach alpha were indicated if any item were to be deleted. Inter-item correlations ranging from .154 to .419 and squared multiple correlations ranging from .110 to .277 were obtained for the *Conscientiousness* subscale. The *Neuroticism* subscale also displayed a range of weak inter-item correlations (.125 to .484) and squared multiple correlations (.089 to .270). For both these subscales no substantial increases in Cronbach's alpha would have been incurred if any of the items had been removed.

In conclusion, no poor items were identified after inspection of the five sets of item statistics and all items were retained for further data analysis.

3.5.3.2. Confirmatory factor analysis

3.5.3.2.1 Measurement model specification and data normality

SEM was used to perform CFA on the set of indicator variables for the Mini-IPIP. The measurement model was specified to consist of 20 observed variables (X's) and five unmeasured latent factors (ξ's, i.e. the Mini-IPIP subscales) with single-headed arrows from the ξ's to the X's representing the proposed regression of the observed variables onto the latent factors (λ s).

The univariate and multivariate normality of the indicator variables for the five subscales were evaluated via PRELIS (Jöreskog & Sörbom, 1996a). The null hypothesis of multivariate normality was rejected (skewness and kurtosis: $\chi2$ = 284.140, p = .000). Consequently, Robust Maximum Likelihood estimation (RML) was employed to derive the model parameter estimates (Mels, 2003). This technique necessitated the computation of an asymptotic covariance matrix via PRELIS to enable the calculation of more appropriate fit indices in LISREL (Mels, 2003).

Table 3.6

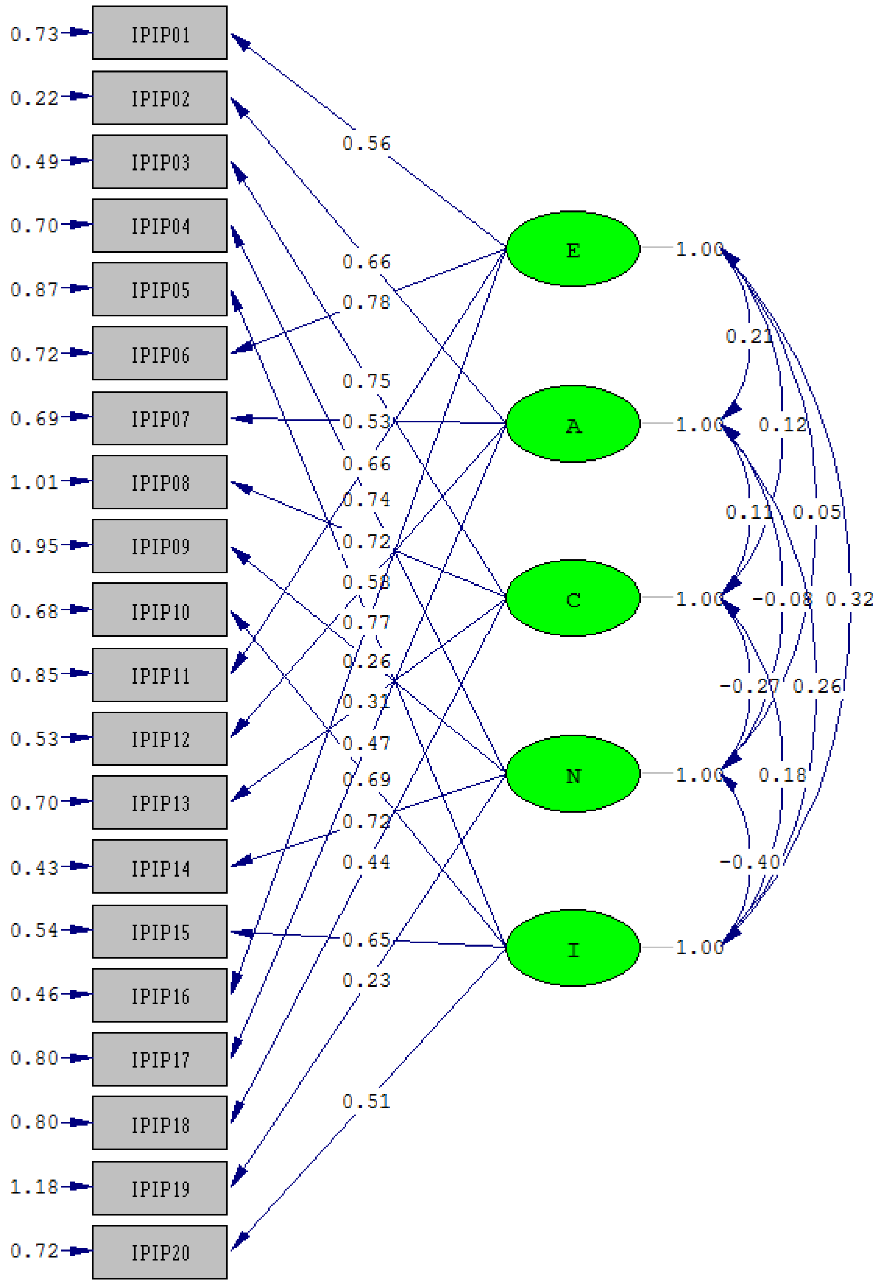
Test of multivariate normality (Mini-IPIP)

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
70.901	13.581	0.000	484.282	7.981	0.000	**248.140**	**0.000**

3.5.2.2.2 Evaluation of the measurement model

The measurement model, in this instance, represented the relationship between the *Extraversion, Agreeableness, Neuroticism, Conscientiousness* and *Intellect/Imagination (Openness to Experience)* latent variables and its manifest indicators. The aim of the CFA was to determine whether the operationalisation of the five latent variables were successful. The operationalisation of the scales could be regarded as successful if the measurement model successfully reproduced the observed covariance matrix, i.e. if the model fitted the data well, if factor loadings were statistically significant ($p < .05$) and sufficiently large ($\lambda > .40$)[29], and if the error variances were sufficiently small. A visual representation of the fitted Mini-IPIP measurement model is shown in figure 3.1.

[29] According to Brown (2015) the issue of what constitutes a sufficiently large factor loading varies across empirical contexts. He suggests that a minimum of .30 or .40 is commonly set for applied factor analytic research on questionnaires. In this chapter completely standardised factor loadings will be considered sufficiently large if λ = .40 or above.



Chi-Square=276.62, df=160, P-value=0.00000, RMSEA=0.060

Figure 3.1. **Measurement model of the Mini-IPIP subscales (standardised solution)**

The results of the single group CFA conducted via LISREL 8.80 (Jöreskog & Sörbom, 2002) for the measurement model of the Mini-IPIP are reported in table 3.7. The exact fit of the Mini-IPIP measurement model was tested by evaluating the S-B $\chi 2$ statistic. A Satorra-Bentler Scaled chi-square value of 276.623 with 160 degrees of freedom and p = .00 was achieved. Thus, implying that the null hypothesis of exact fit (RMSEA = 0) was rejected ($p < .05$). The assumption of exact fit is highly unlikely, and therefore, the rejection of the exact fit null hypothesis was not surprising.

Consequently, the null hypothesis of close fit was tested by LISREL and is shown in table 3.7 as the P-Value for Test of Close Fit (RMSEA < .05) = .0882. The close fit null hypothesis was not rejected and it was concluded that the measurement model obtained close fit. According to Hair et al. (2006) a model with 20 observed variables, tested on a sample of less than 250, should obtain a CFI of at least .95 to be indicative of good fit. The SRMR and RMSEA should be smaller than .08 (Hair et al., 2006). The CFI value of .876 in this instance is indicative of mediocre model fit. However, the SRMR (.0791) and RMSEA (.0598) are deemed as indicating reasonable to good model fit.

All the factor loadings were statistically significant ($t \geq 1.64$). From the lambda-X completely standardised solution, it was evident that the factor loadings generally ranged from .405 (item IPIP05 = *Intellect/Imagination*) to .817 (item IPIP02 = *Agreeableness*), with exception of three factor loadings being below .40. This included items IPIP09 (*Neuroticism*), IPIP13 (*Conscientiousness*) and IPIP19 (*Neuroticism)* with loadings of .259, .350 and .209[30], respectively. In conclusion, the basket of results seemed to suggest that reasonable to acceptable model fit was achieved.

Table 3.7

Goodness of fit statistics for the Mini-IPIP measurement model

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	310.667 (P = 0.00)

[30] Due to the limited number of items per subscale (m = 4), these items were not considered for deletion.

Satorra-Bentler Scaled Chi-Square (S-Bχ2)	276.623 (P = 0.000)
Degrees of Freedom	160
S-Bχ2/ df	1.729
Non-Normed Fit Index (NNFI)	0.853
Comparative Fit Index (CFI)	0.876
Root Mean Square Residual (RMR)	0.0835
Standardised RMR	0.0791
Root Mean Square Error of Approximation	0.0598
90 Percent Confidence Interval for RMSEA	(0.0477; 0.0715)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.0882

3.5.4 Sensation Seeking

The Brief Sensation Seeking Scale (BSSS), developed by Hoyle, Stephenson, Palmgreen, Lorch, and Donohew (2002), was used to measure *Sensation Seeking*. It is a brief self-report measure, comprising a set of eight items based on the Zuckerman's Sensation Seeking Scale Form V (SSS-V) (Zuckerman, Kolin, Price, & Zoob, 1964). *Sensation Seeking*, as measured by this instrument, is defined as the need for varied, new, and complex sensations and experiences and the willingness to take physical and social risks for the sake of such experiences. Each of the four dimensions, i.e. thrill and adventure seeking, experience seeking, disinhibition and boredom susceptibility in the SSS-V, are represented by two items in the BSSS.

The BSSS was validated across a set of two studies by Hoyle et al. (2002) and produced an internal consistency of .76 for the eight-item set in the first study. Similarly, the internal consistency was acceptable ranging from .75 to .78 in the second study. A CFA was conducted to determine the structural validity of the measure. A good latent variable representation (i.e. one factor model) of the *Sensation Seeking* construct was produced (average loading = .63, RMSEA = .017). Moreover, the BSSS displayed predictive validity and mirrored the full content domain of the parent version, the SSS-V (Hoyle et al., 2002).

Participants were expected to rate how well each of the items (in sentence fragment form) describe them, using a five-point scale ranging from "strongly disagree" to "strongly agree".

3.5.4.1 Descriptive statistics and item analysis

Item analyses of the BSSS revealed a reliability coefficient of .764. This fell comfortably above the generally accepted, yet arbitrary, cut-off point (.70) stipulated by Nunnaly (1978). After inspection of the item analysis statistics, item BSS07 was flagged as a possible poor item.

The inter-item correlation matrix indicated that the inter-item correlations of BSS07 (ranging from .064 to .601) were generally lower in comparison to those of the other items. The deletion of this item would have incurred an increase, albeit very small, in the Cronbach's alpha (Δ = .001) resulting in .765. Based on this marginal increase, it was decided not to delete the item. The scale is already very short and therefore, it was argued that it would not be sensible to delete item BSS07 from the item pool.

Table 3.8

The mean, standard deviation and reliability statistics for the BSSS

BSSS	Number of items	M	SD	A
BSSS	8	24.64	5.912	.764

Note: BSSS = Brief Sensation Seeking Scale

3.5.4.2 Confirmatory factor analysis

3.5.4.2.1 Measurement model specification and data normality

SEM was used to perform CFA on the BSSS measurement model which was specified to consist of eight observed variables (X's) and one unmeasured latent factor (ξ, i.e. *Sensation Seeking*) with single-headed arrows from the ξ to the X's representing the proposed regression of the observed variable onto the latent factor (λ s).

The univariate and multivariate normality of the indicator variables were investigated via PRELIS (Jöreskog & Sörbom, 1996a). The null hypothesis of multivariate normality was rejected (skewness and kurtosis: $\chi 2$ = 35.374, p = .000). RML estimation was employed to derive the model parameter estimates.

Table 3.9

Test of multivariate normality (BSSS)

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
6.322	5.072	0.000	85.692	3.106	0.002	**35.374**	**0.000**

3.5.4.2.2 Evaluation of the measurement model

The measurement model, in this instance, represented the relationship between the *Sensation Seeking* variable and its manifest indicators. The aim of the CFA was to determine whether the operationalisation of the latent variable, i.e. *Sensation Seeking* was successful. A graphical representation of the BSSS measurement model is presented in figure 3.2.

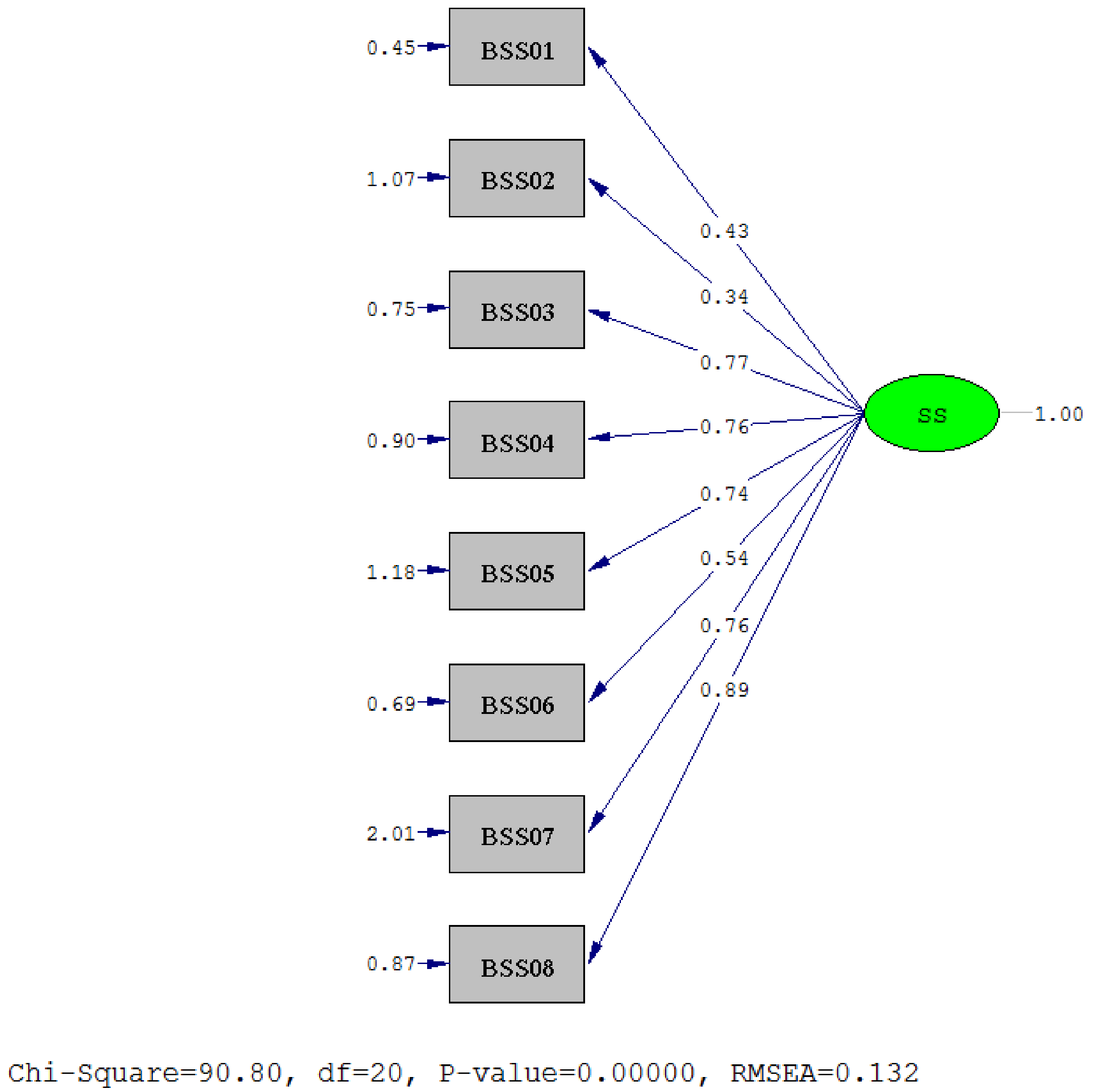


Figure 3.2. **Measurement model of the BSSS (standardised solution)**

The results of the CFA conducted with LISREL 8.80 (Jöreskog & Sörbom, 2002) are reported in table 3.10. The exact fit of the BSSS measurement model was tested by evaluating the S-B $\chi 2$ statistic. A Satorra-Bentler Scaled chi-square value of 90.792 with 20 degrees of freedom and p = .00 was achieved. Thus, implying that the null hypothesis of exact fit (RMSEA = 0) should be rejected ($p < .05$).

The null hypothesis of close fit was tested by LISREL and is shown in table 3.10 as the P-Value for Test of Close Fit (RMSEA < .05) = .000. Consequently, the close fit null hypothesis was rejected and it was concluded that the measurement model did not obtain close fit. When a sample has a magnitude of less than 250 with items equal to or less than 12 observed variables, as is the case in the current research study, the CFI and NNFI should be greater than .97 to ensure that a misspecified model is not accepted. In addition, Hair et al. (2006) suggested that the SRMR and RMSEA should be smaller than .08. The CFI value of .880 and NNFI of .832 in this instance were well below the suggested cut-off values. The SRMR (.0845) marginally missed the cut-off value. The RMSEA (.132) and the lower boundary of the 90 percent confidence interval were above the suggested cut-off value. Of the eight items, all but one, item BSS02 (.315) obtained significant factor loadings above .40 ($t \geq 1.64$). The completely standardised loadings ranged from .474 to .691.

Table 3.10

Goodness of fit statistics for the BSSS measurement model

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	112.581 (P = 0.00)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	90.792 (P = 0.00)
Degrees of Freedom	20
S-Bχ2/ df	4.5396
Non-Normed Fit Index (NNFI)	0.832
Comparative Fit Index (CFI)	0.880
Root Mean Square Residual (RMR)	0.133
Standardised RMR	0.0845
Root Mean Square Error of Approximation	0.132
90 Percent Confidence Interval for RMSEA	(0.105; 0.160)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.000

Based on this basket of evidence presented above, mediocre fit was concluded and the uni-dimensionality of the items was questioned. After considering the fact that the measure was developed with the intention of retaining the same basic content structure of Zuckerman's Sensation Seeking Scale Form-V, it was decided to conduct a multi-dimensional CFA. In this instance the model was specified to consist of four unmeasured latent factors (ξ' s). Each of the four dimensions, i.e. thrill and adventure seeking, experience seeking, disinhibition and boredom susceptibility in the SSS-V are represented by two items in the BSSS. A graphical representation of the BSSS measurement model is presented in figure 3.3.

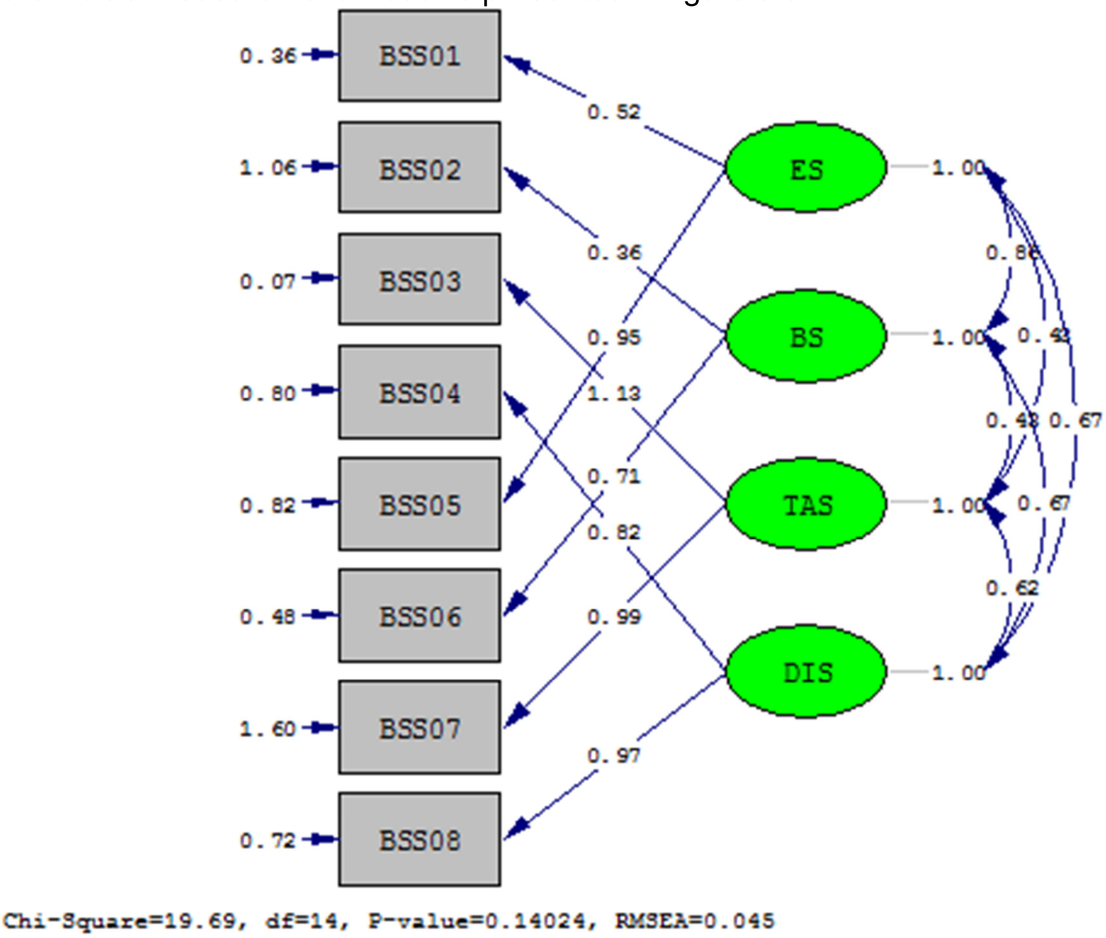


Figure 3.3. **Measurement model of the BSSS (standardised solution; multi-dimensional)**

Table 3.11 summarises the fit indices obtained for the measurement model. This model achieved a Satorra-Bentler Scaled chi-square value of 19.689 with 14 degrees of freedom and p = .140 (table 3.11). Thus, implying that the null hypothesis of exact fit should not be rejected (p > .05). It can be concluded that the measurement model provides a perfect account of the manner in which the latent variables manifest themselves in the indicator variables. All other fit indices reported in table 3.11 corroborated the inference of a well-fitting measurement model. The completely standardised factor loadings revealed that all of the items obtained significant factor loadings above .40 ($t \geq 1.64$) and ranged from .618 to .973, with exception of one factor loading being below .40. This was item BSS02, with a factor loading of .330.

Table 3.11

Goodness of fit statistics for the BSSS measurement model (multi-dimensional)

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	23.020 (P = 0.0599)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	19.689 (P = 0.140)
Degrees of Freedom	14
S-Bχ2/ df	1.4064
Non-Normed Fit Index (NNFI)	0.981
Comparative Fit Index (CFI)	0.990
Root Mean Square Residual (RMR)	0.0554
Standardised RMR	0.0381
Root Mean Square Error of Approximation	0.0446
90 Percent Confidence Interval for RMSEA	(0.0; 0.0869)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.534

3.5.5 Emotional regulation (Emotional Self-Control and Emotional Self-Management)

The third measure that was utilised is the Genos Emotional Intelligence Inventory (Genos EI) developed by Dr Gilles Gignac (Gignac, 2010). It is a self-report inventory designed to measure the frequency with which an individual displays emotionally intelligent behaviours. The Genos EI comprises seven subscales with 10 items each. The seven subscales are: (1) *Emotional Self-Awareness*, (2) *Emotional Expression*, (3) *Emotional Awareness of Others*, (4) *Emotional Reasoning*, (5) *Emotional Self-Management*, (6) *Emotional Management of Others*, and (7)

Emotional Self-Control. For the purposes of this research, the subscales *Emotional Self-Management*, defined as the relative frequency with which individuals manage their own emotions successfully, and *Emotional Self-Control*, defined as the relative frequency with which individuals control their strong emotions appropriately, were used.

Gignac (2010) has shown adequate factor structure and internal consistency for the Genos EI across several samples of individuals associated with five nationalities, i.e. American, Asian, Australian, Indian and South African. The total EI scale scores displayed high levels of internal consistency reliabilities ranging from .94 to .97. Similarly, the subscale scores also yielded respectable internal consistency reliabilities ranging from .71 to .85. Moreover, the test-retest reliabilities calculated for two samples across two and eight months yielded reliabilities of .83 and .72, respectively, for the total EI scale scores. Thus, the Genos EI indicates acceptable stability over time. Similar results were obtained for the subscale scores at .77 and .66, respectively. A study by Gignac and Ekermans (2010) in which they analysed the psychometric properties of the Genos EI within a sample of Black and White South Africans, provide further support for its psychometric strength. The internal consistency reliabilities were relatively high and similar across samples, yielding values of approximately .94 for the total scores. The subscales produced internal consistency reliabilities in excess of .69 and the two groups obtained similar means and standard deviations. Based on differential item functioning (DIF) analysis only three out of the 70 items were shown to be biased. However, the magnitudes of the bias were neglected based on DIF plots. In light of this, it could be concluded that the Genos EI is not culturally biased against Whites or Blacks, which proves to be valuable for use within the South African context. There exists critique against the *Emotional Reasoning* scale, urging for its revision due to its poor psychometric properties. For purposes of this study, however, this does not provide a cause for concern, as only two Genos EI subscales were included in the current study, namely (1) *Emotional Self-Management*, and (2) *Emotional Self-Control*.

Moreover, the measure has shown good convergent validity with its predecessor, the SUIET (Palmer & Stough, 2001), with a disattenuated correlation of .93 and an attenuated correlation of .78, suggesting that they measure similar (albeit not exactly the same) constructs. The Genos EI also displayed respectable convergent validity with the Trait Meta Mood Scale (Salovey, Mayer, Goldman, Turvey, & Palfai, 1994), with a correlation of .50 between its total scores. Furthermore, the Genos EI demonstrated positive correlations with job satisfaction, organisational commitment as well as transformational leadership, and a negative correlation with laissez-faire leadership as measured by the MLQ - thereby implying incremental validity (Gignac, 2010). Based on two studies that measured job performance, it furthermore demonstrated appreciable predictive validity. Discriminant validity was displayed by its failure to correlate substantially with socially desirable responses and transactional leadership style, and although there are moderately sized correlations between several personality dimensions and the Genos EI, the Genos EI is associated with a sufficient amount of unique factorial validity to counter beliefs of construct redundancy.

Participants were asked to respond to each item on a five-point Likert scale ranging from “almost never” to “almost always”.

3.5.5.1 Descriptive statistics and item analyses

The Genos Emotional Intelligence Inventory consists of seven subscales measuring seven latent constructs that combine to form the construct of emotional intelligence. Thus, although these scales are expected to correlate to some degree, they measure qualitatively distinct latent variables. Respondents can thus obtain a high score on one dimension without necessarily obtaining a similar score on another dimension. If the coefficient of internal consistency were to be calculated on the whole scale, it would imply the expectation of a high internal consistency in item responses across the entire set of scale items. In this research, however, it was more theoretically credible to expect that there should be a high internal consistency in item responses across the items comprising each individual subscale, as only a subset of two of the sub-dimensions of the full emotional intelligence scale was utilised. Hence, item analyses were only conducted on the two separate subscales presented in the structural model, i.e. *Emotional Self-management* and *Emotional Self-control.* The results obtained via the scale reliability procedure in SPSS Version 22.0 (IBM Corp, 2013) are presented in table 3.12. The results of the item analyses indicated that the two subscales have good internal consistency, with α = .737 and

.715 respectively.

The inter-item correlation matrix of the *Emotional Self-management* subscale revealed low inter-item correlations ranging from .044 to .427. The squared multiple correlations were also small and ranged from .131 to .314. However, no item, if deleted, would have resulted in a substantial increase in Cronbach's alpha. In the *Emotional Self-control* subscale one item, ER12, was flagged as a possible poor item. This conclusion was reached after an inspection of the item-total statistics and more specifically the squared multiple correlations. This item had the lowest squared multiple correlation (.094). The residual nine items had squared multiple correlations ranging from .112 to .336. However, the inter-item correlations for this item were not much lower than the rest. The results revealed that the deletion of this item would result in a marginal increase of the Cronbach's alpha from .715 to .724. Due to the fact that the initial Cronbach's alpha for this subscale was acceptable, and the fact that the squared multiple correlation and inter-item-correlations relating to the item were not significantly lower than that of the other items, it was decided to protect the integrity of the original scale and not delete the item from the subscale. All items were thus retained and utilised in subsequent analyses.

Table 3.12

The means, standard deviation and reliability statistics for the Genos EI subscales

Genos EI subscale	Number of items	M	SD	α
ESM	10	37.44	4.611	.737
ESC	10	37.72	4.603	.715

Note: ESM = Emotional Self-Management; ESC = Emotional Self-Control.

3.5.5.2 Confirmatory factor analysis

SEM was used to perform separate confirmatory factor analysis on the set of indicator variables for the two individual subscales of the Genos Emotional Intelligence Inventory used in this research, i.e. *Emotional Self-Management* and *Emotional Self-Control.*

3.5.5.2.1 Emotional Self-Management

3.5.5.2.1.1 Measurement model specification and data normality

The null hypothesis of multivariate normality was rejected (skewness and kurtosis: $\chi 2$ = 175.172, p = .000). Once again RML estimation was employed to derive the model parameter estimates.

Table 3.13

Test of multivariate normality (Emotional Self-Management subscale)

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
15.652	10.874	0.000	144.512	7.546	0.000	**175.172**	**0.000**

3.5.5.2.1.2 Evaluation of the measurement model

The measurement model, in this instance, represented the relationship between the latent variable, *Emotional Self-Management* and its manifest indicators. The operationalisation of the scale could be regarded as successful if the measurement model successfully reproduced the observed covariance matrix, i.e. if the model fitted the data well, if factor loadings were statistically significant ($p < .05$) and sufficiently large ($\lambda > .40$), and if the error variances were sufficiently small. A visual representation of the fitted measurement model is shown in figure 3.4 and the overall fit statistics are presented in table 3.14.

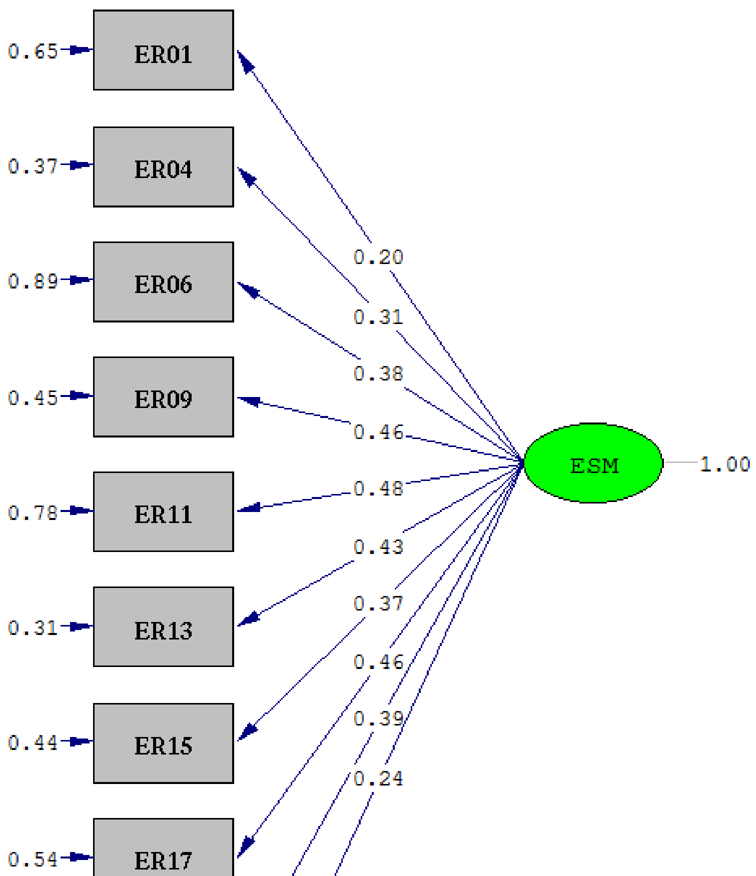


Figure 3.4**. Measurement model of the Emotional Self-Management subscale (standardised solution)**

The exact fit null hypothesis of the measurement model was tested by means of the Satorra-Bentler scaled chi-square (S-B χ^2) statistic, which achieved a value of 53.080 with 35 degrees of freedom and p = .0257. Thus, implying that the null hypothesis of exact fit (RMSEA = 0) should be rejected ($p < .05$). To assess whether the model displayed an approximate fit of the processes that operate in reality, the P-Value for Test of Close Fit (RMSEA < .05) = .464 was considered. For this model, the close fit null hypothesis was not rejected and close fit was concluded. In this instance, with a sample magnitude of less than 250 with between 12 and 30 observed variables, the CFI and NNFI should be greater than .95 to ensure that an incorrectly specified model is not accepted. In addition, the SRMR and RMSEA should be smaller than .08 (Hair et al., 2006). The CFI value of .955 and NNFI of .942, although marginally lower, met the suggested cut-off values. The SRMR (.0616) and the RMSEA (.0503) were comfortably below the suggested cut-off value. Three of the completely standardised factor loadings obtained values lower than .40, ranging from .244 to .375. The remaining seven items obtained significant factor loadings above this value. These loadings ranged from .412 to .612. Based on this basket of evidence, close fit was concluded.

Table 3.14

Goodness of fit statistics for the Emotional Self-Management Scale of the Genos Emotional Intelligence Inventory

Goodness of Fit Statistics

Normal Theory Weighted Least Squares Chi-Square	66.513 (P = 0.00149)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	53.080 (P = 0.0257)
Degrees of Freedom	35
S-Bχ2/ df	1.5166
Non-Normed Fit Index (NNFI)	0.942
Comparative Fit Index (CFI)	0.955
Root Mean Square Residual (RMR)	0.0456
Standardised RMR	0.0616
Root Mean Square Error of Approximation	0.0503
90 Percent Confidence Interval for RMSEA	(0.0181; 0.0765)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.464

3.5.5.2.2 Emotional Self-Control

3.5.5.2.2.1 Measurement model specification and data normality

The null hypothesis of multivariate normality was rejected (skewness and kurtosis: $\chi 2$ = 268.160, p = .000) and RML estimation was employed to derive the model parameter estimates.

Table 3.15

Test of multivariate normality (Emotional Self-Control Scale)

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
19.721	14.261	0.000	147.258	8.049	0.000	**268.160**	**0.000**

3.5.5.2.2.2 Evaluation of the measurement model

The measurement model, in this instance, represented the relationships between the latent variable, *Emotional Self-Control* and its manifest indicators. A visual representation of the fitted measurement model is shown in figure 3.5 and the overall fit statistics are presented in table 3.16.

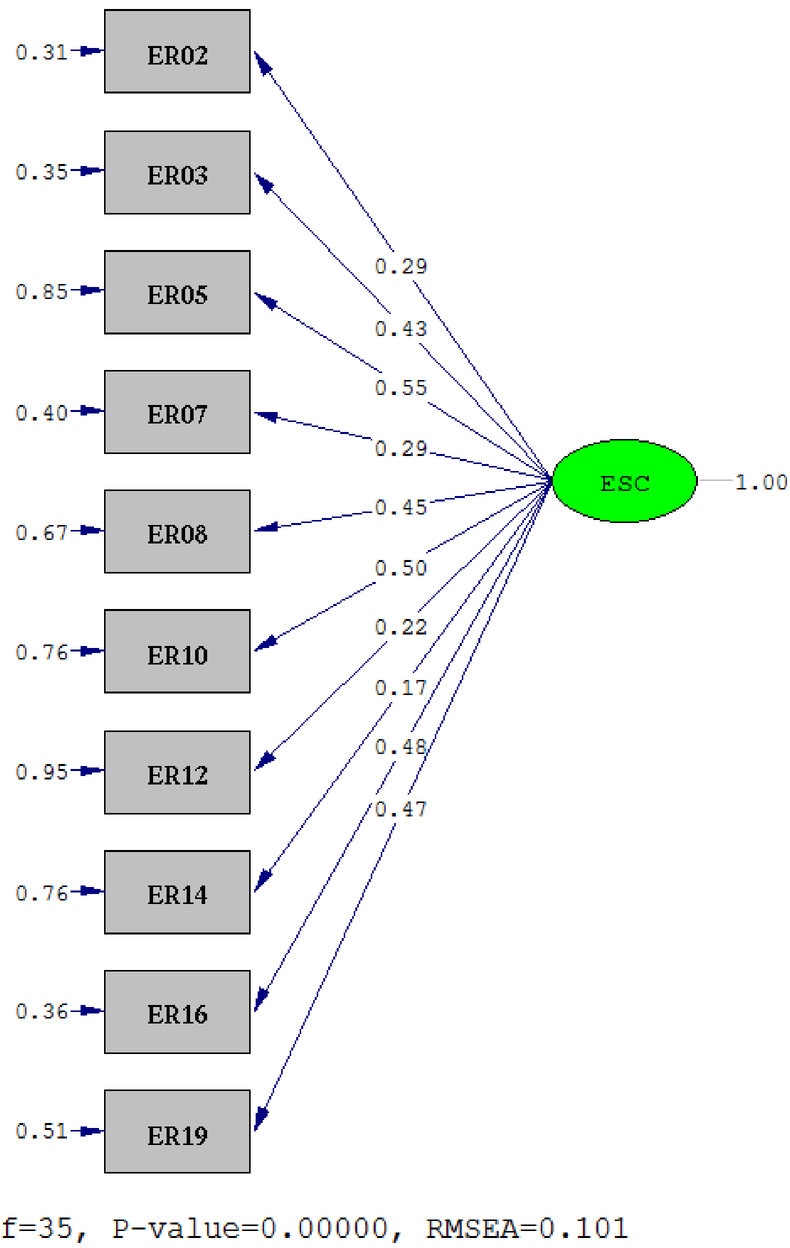


Figure 3.5. **Measurement model of the Emotional Self-Control subscale (standardised solution)**

The Satorra-Bentler scaled chi-square (S-B χ^2) statistic achieved a value of 108.423 with 35 degrees of freedom and p = .00. Thus, the null hypothesis of exact fit (RMSEA = 0) was rejected (p < .05). To assess whether the model displayed close fit, the P-Value for Test of Close Fit (RMSEA < .05) = .000 was considered. For this model, the close fit null hypothesis was rejected and close fit was not concluded. The CFI value of .850 and NNFI of .797 fell well below the cut-off values suggested by Hair et al. (2006). In addition, the SRMR (.0807) and the RMSEA (.101) exceeded the proposed cut-off value. Eight of the items comprising the ten-item subscale obtained significant factor loadings above .40. The completely standardised factor loadings ranged from .417 to .628.

Table 3.16

Goodness of fit statistics for the Emotional Self-Control subscale of the Genos Emotional Intelligence Inventory

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	118.780 (P = 0.00)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	108.423 (P = 0.00)
Degrees of Freedom	35
S-Bχ2/ df	3.0978
Non-Normed Fit Index (NNFI)	0.797
Comparative Fit Index (CFI)	0.850
Root Mean Square Residual (RMR)	0.0632
Standardised RMR	0.0807
Root Mean Square Error of Approximation	0.101
90 Percent Confidence Interval for RMSEA	(0.0801; 0.123)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.000

3.5.5.2.2.3 Exploratory factor analysis

The CFA results for the *Emotional Self-Control* measurement model did not indicate good fit. Consequently, EFA was conducted on the original *Emotional Self-Control* scale to investigate the factor structure of the subscale in the current sample. Firstly, an unrestricted EFA using principal component analysis (PCA) with Varimax rotation was conducted on the ten-item scale, i.e. SPSS was allowed to freely determine the number of factors to extract. The Eigen-value-greater-than-one rule and the scree plot suggested the extraction of three factors accounting for 55.043% of the total variance. The rotated factor matrix of the unrestricted EFA can be viewed in table 3.17.

Table 3.17

Rotated factor matrix of the Emotional Self-Control subscale of the Genos Emotional Intelligence Inventory (free EFA)

	Factors		
	1	**2**	**3**
ESC2	**.733**	-.109	.108
ESC3	**.619**	.307	-.149
ESC5	.193	**.689**	.299
ESC7	**.706**	-.197	.261
ESC8	.418	**.456**	-.179
ESC10	.175	**.741**	.124
ESC12	.053	.151	**.880**
ESC14	-.139	**.637**	-.023
ESC16	**.666**	.307	-.160
ESC19	**.550**	.263	.258

Note: Values in bold represent significant factor loadings.

An investigation of the non-redundant residuals with absolute values greater than .05 revealed a value of 82% for this solution. This was unacceptably high and pointed towards the fact that the rotated factor solution did not provide a credible explanation for the observed inter-item correlation matrix. Further investigation revealed that five of the ten items loaded acceptably onto Factor 1 (> .40), with four items loading onto Factor 2 (> .40). However, a single item, ESC12, loaded onto the third extracted factor. Given the concerning item statistics for this item (discussed in section 3.5.5.1), as well as this result, it was decided to delete this item from the item pool. The EFA was rerun using principal axis factoring (PAF)[31] with Varimax rotation, and

[31] Both PCA and PAF was used as extraction techniques. However, PAF yielded superior results and provided the best defined factor structure. According to Hooper (2012) PAF is superior to PCA as its goal is to find the latent structure of the dataset by uncovering common factors and thus, analyses common variance, which is more suitable when exploring underlying theoretical constructs. In contrast to this, PCA is essentially a data reduction method and reduces the measured variable to a smaller set of composite components that capture as much information as possible in as few components as possible.

a two factor solution was forced onto the data. The results of the repeated analysis are displayed in table 3.18.

The two factors explained 48.89% of the variance. After an investigation of the non-redundant residuals with absolute values greater than .05 for the two-factor solution, it was noted that it was acceptable at 13%. This suggested that the two-factor solution provided a permissible account of the factor structure of the scale within this particular sample. From the results in table 3.18, it was evident that items ESC2, ESC3, ESC7, ESC16, and ESC19 loaded significantly onto Factor 1, while items ESC5, ESC8, ESC10 and ESC14 loaded onto Factor 2. The item content of both factors was investigated and no meaningful underlying theoretical themes emerged. However, upon closer inspection it became clear that the items were worded as such that they could be grouped into positively and negatively worded units. Thus, the presence of a method bias was considered, in which the wording of the items could have resulted in differential response styles from participants. Factor one consisted of positively worded items such as “I respond to events that frustrate me appropriately”. Factor two consisted of negatively worded items such as “I fail to control my temper at work”. However, it should be noted that item ESC19 was the only exception to this rule in that it was negatively phrased but loaded onto Factor 1.

Table 3.18

Rotated factor matrix of the Emotional Self Control subscale of the Genos Emotional Intelligence Inventory (forced two-factor EFA)

	Factors	
	1	**2**
ESC2	**.637**	-.012
ESC3	**.499**	.280
ESC5	.199	**.631**
ESC7	**.616**	-.077
ESC8	.333	**.348**
ESC10	.165	**.693**
ESC14	-.054	**.391**
ESC16	**.563**	.284
ESC19	**.478**	.271

Note: Values in bold represent significant factor loadings.

Based on the original design intention of the scale and the fact that the proposed structural model treated *Emotional Self-Control* as a single, undifferentiated latent variable, the factor analysis was repeated, and the extraction of a single factor was forced. The results are displayed in table 3.19. Even though all but one of the items achieved loadings greater than .40, the single factor structure accounted for only 32.66% of the variance.

The residual correlations were computed for the one factor solution. Fifty percent of the non-redundant residuals had absolute values greater than .05, which was significantly higher than the 13% obtained for the two-factor solution. Thus, it could reasonably be concluded that a general single factor was not more strongly supported by the results, than a two-factor solution. Consequently, a CFA was conducted on the derived two-factor solution.

Table 3.19

Factor matrix of the Emotional Self-Control subscale of the Genos Emotional Intelligence Inventory (forced one-factor EFA)

	Factor
	1
ESC2	.467
ESC3	.582
ESC5	.508
ESC7	.410
ESC8	.488
ESC10	.502
ESC14	.195
ESC16	.635
ESC19	.555

3.5.5.2.2.4 Confirmatory factor analysis

A visual representation of the fitted measurement model is shown in figure 3.6. The CFA on the derived two-factor structure yielded significantly improved results.

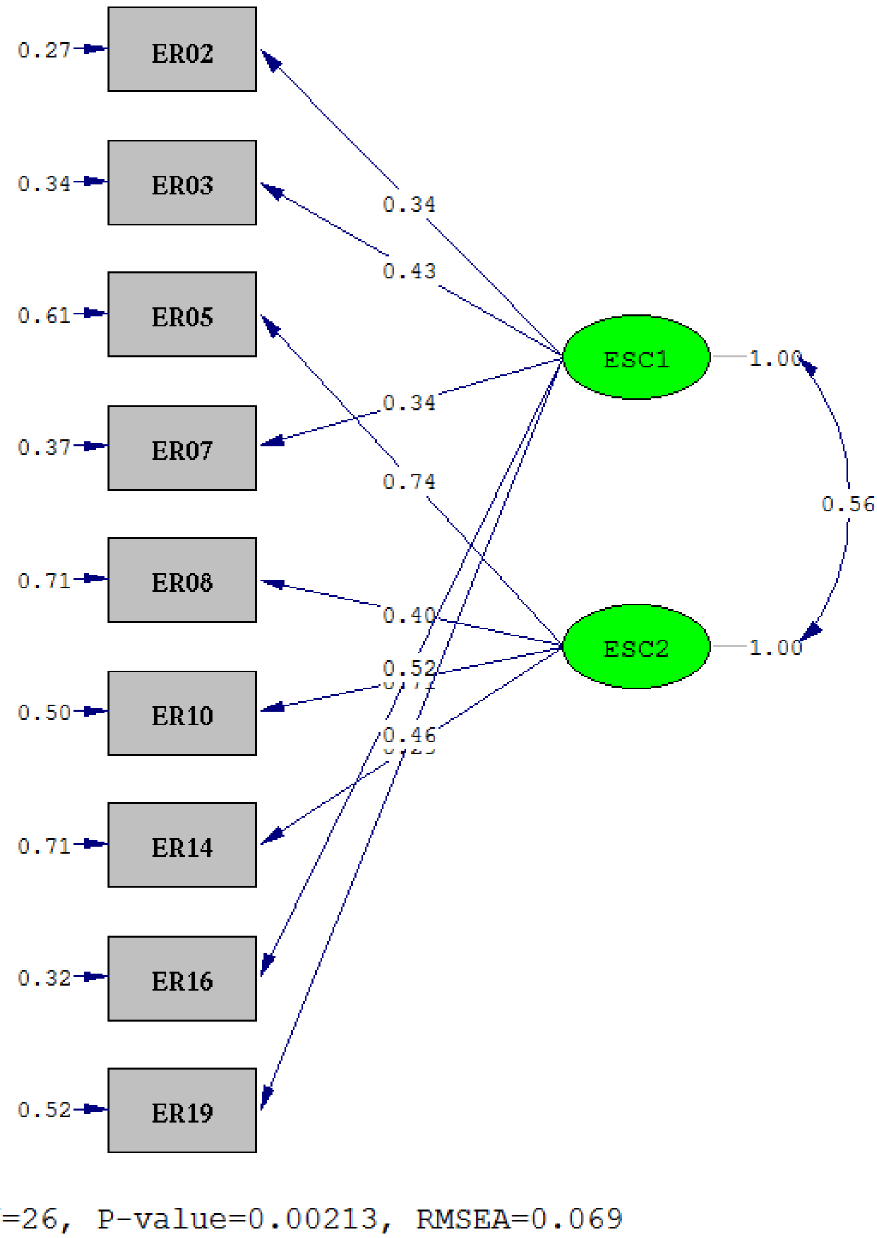


Figure 3.6. **Two factor measurement model of the Emotional Self-Control subscale (standardised solution)**

A Satorra Bentler Scaled chi-square value 51.408 with 26 degrees of freedom and p = .00213 was obtained. Thus, the null hypothesis of exact fit was rejected ($p < .05$). A RMSEA of .0692 indicated good model fit in the sample. The probability of obtaining this sample RMSEA value under the assumption that the model fits closely in the population was sufficiently high at .122, so as not to discard the assumption as permissible (i.e. close fit was achieved).

The other Goodness-of-fit indices improved significantly, compared to the original one-dimensional CFA model results. The CFI increased from .850 to .925. The NNFI increased from .797 to .898. Even though both these values still fell below the suggested cut-off of .97 by Hair et al. (2006), it was concluded, based on the basket of evidence attained, that the two-factor model provided a better account of the structure of the instrument in this particular sample. The completely standardised factor loadings were all significant and ranged from .431 to .710, with the exception of one item (ESC14) with a factor loading of .324.

Table 3.20

Goodness of fit statistics for the reduced Emotional Self-Control subscale of the Genos Emotional Intelligence Inventory

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	54.420 (P = 0.000898)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	51.408 (P = 0.00213)
Degrees of Freedom	26
S-Bχ2/ df	1.977
Non-Normed Fit Index (NNFI)	0.898
Comparative Fit Index (CFI)	0.925
Root Mean Square Residual (RMR)	0.0479
Standardised RMR	0.0717
Root Mean Square Error of Approximation	0.0692
90 Percent Confidence Interval for RMSEA	(0.0407; 0.0969)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.122

3.5.6 Delay of Gratification

The fourth measure utilised in this research study was the Delaying Gratification Inventory (DGI), developed by Hoerger, Quirk, and Weed (2011). According to these scholars "delaying gratification refers to the tendency to forego strong immediate satisfaction for the sake of salient long-term rewards" (Hoerger et al., 2011, p. 725). It is a 35-item scale that produces gratification delay scores for five domains (food, physical pleasure, social interactions, money and achievement). However, for purposes of this study, only the money subsection, consisting of seven items, was utilised.

Hoerger et al. (2011) validated the DGI across a series of four studies. The studies yielded evidence of the DGI as a psychometrically strong measure of delay of gratification. Scores on the DGI demonstrated respectable internal consistency reliabilities and test-retest reliability for the 35-item DGI composite, the five domains, as well as 10-item short-form. Internal consistency reliabilities ranged from .71 (physical dimension) to .89 (money dimension) for the subscales and reached a value of .91 for the DGI-35 composite. Test-retest reliability ranged from $r = .74$ (food and social dimension) to $r = .90$ (money dimension and DGI-35 composite) (Hoerger et al., 2011).

Furthermore, evidence was obtained that the five-factor structure fitted the data well. Evidence for construct validity was obtained by correlations with scores on closely related constructs measured by self-control measures, behavioual ratings, Big Five personality trait measures and several constructs on the MMPI-2-RF. Incremental validity was supported by obtaining correlations with well-being and health-related variables (Hoerger et al., 2011).

Participants were expected to rate how well each of the items (in sentence fragment form) contained in the Money DGI subscale describe them, using a five-point Likert scale ranging from “strongly disagree” to “strongly agree”.

3.5.6.1 Descriptive statistics and item analysis

The internal consistency (.776) of the DGI was good, as illustrated in the summary of the item analysis results and descriptive statistics in table 3.21.

The item statistics were reviewed and the results indicated that the removal of item DGI02 would result in the greatest, albeit marginal, increase in alpha (from .776 to .781). The squared multiple correlation (.194) of this item was the lowest compared to the others (ranging from .196 to .427). The range of the inter-item correlations (.173 to .363) was also lower. However, given the fact that the scale had already obtained an acceptable reliability coefficient and given the limited number of items (m = 8), it was decided to retain all items for subsequent analyses.

Table 3.21

The means, standard deviation and reliability statistics for the DGI

DGI	Number of items	M	SD	α
DGI	7	30.98	3.834	.776

Note: DGI = Delaying Gratification Inventory

3.5.6.2 Confirmatory factor analysis

3.5.6.2.1 Measurement model specification and data normality

SEM was used to perform CFA on the Money subscale of the Delaying Gratification Inventory (DGI). The measurement model was specified to consist of seven observed variables (X's) and one unmeasured latent factor (ξ; i.e. *Delay of Gratification*) with single-headed arrows from the ξ to the X's representing the proposed regression of the observed variable onto the latent factor (λ s).

The univariate and multivariate normality of the indicator variables were investigated via PRELIS (Jöreskog & Sörbom, 1996a). The null hypothesis of multivariate normality was rejected (skewness and kurtosis: $\chi 2$ = 1066.057, p = .000). RML estimation was employed to derive the model parameter estimates. The measurement model is graphically depicted in figure 3.7.

Table 3.22

Test of multivariate normality (DGI)

	Skewness			Kurtosis		Skewness and Kurtosis	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
40.204	29.958	0.000	122.468	12.984	0.000	**1066.057**	**0.000**

3.5.6.2.2 Evaluation of the measurement model

The measurement model, in this instance, represented the relationship between the *Delay of Gratification* variable and its manifest indicators. The aim of the CFA was to determine whether the operationalisation of the latent variable was successful.

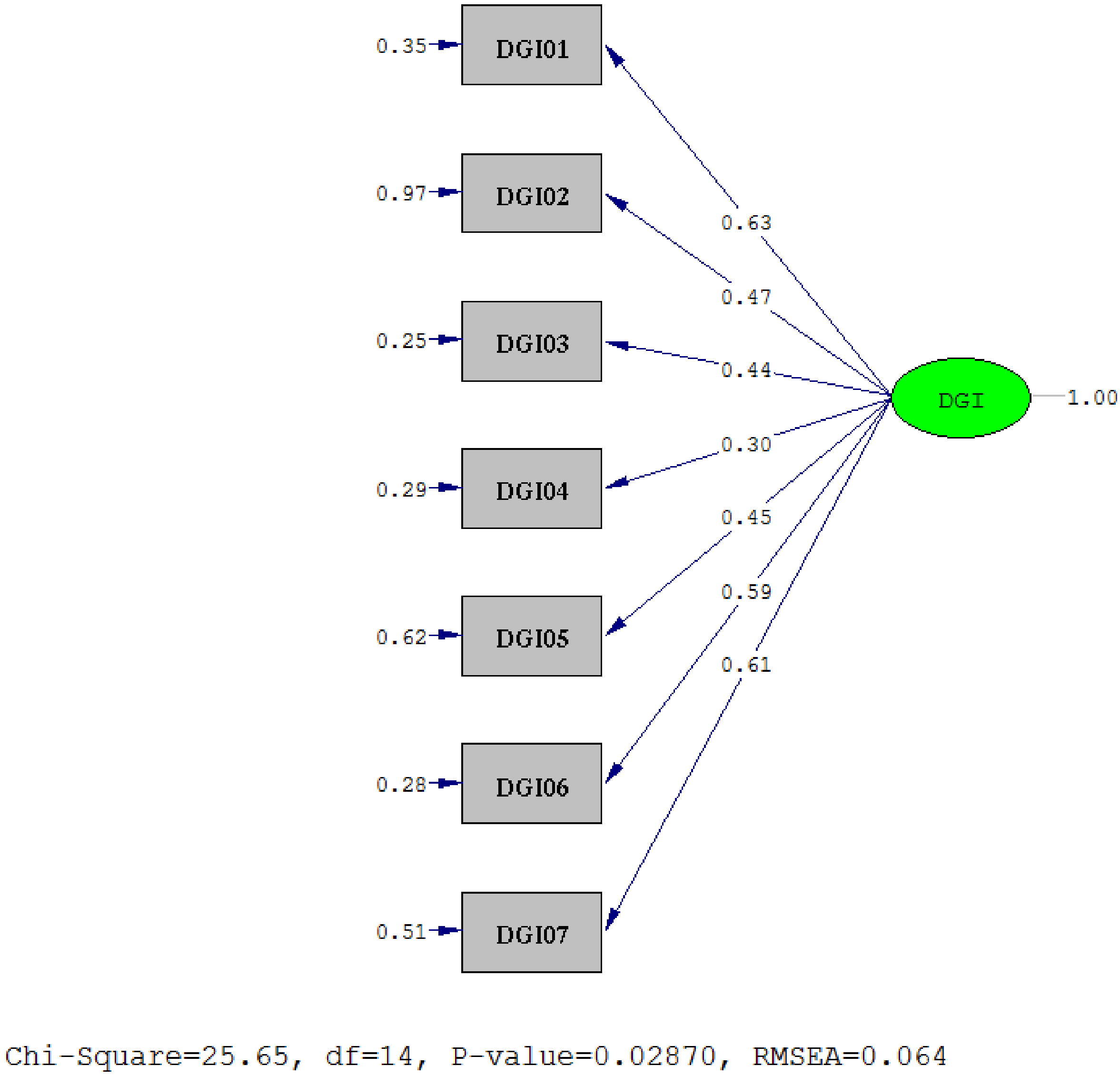


Figure 3.7. **Measurement model of the DGI (standardised solution)**

The results of the CFA are presented in table 3.23. Goodness of fit was evaluated in terms of the Hair et al. (2006) guidelines for models with observed variables equal to or smaller than 12 (refer to table 3.2). A Satorra Bentler-Scaled chi-square value of 25.646 (p. = .0287) with 14 degrees of freedom emerged. Thus, implying that the null hypothesis of exact fit should be rejected ($p < .05$). For this model, close fit was obtained by not rejecting the null hypothesis for close fit ($p = .251$; $p > .05$). Hence, it could be concluded that the position that this model displayed close fit in the parameter was a permissible position. Both the CFI (.980) and NNFI (.969) indicated good model fit. The SRMR value of .0423 was well under .08, as was the RMSEA of .0639, further corroborating this inference. All factor loadings were statistically significant and above the .40 cut-off. These values ranged from .430 to .742.

Table 3.23

Goodness of fit statistics for the DGI measurement model

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	25.213 (P = 0.0325)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	25.646 (P = 0.0287)
Degrees of Freedom	14
S-Bχ2/ df	1.832
Non-Normed Fit Index (NNFI)	0.969
Comparative Fit Index (CFI)	0.980
Root Mean Square Residual (RMR)	0.0335
Standardised RMR	0.0423
Root Mean Square Error of Approximation	0.0639
90 Percent Confidence Interval for RMSEA	(0.0203; 0.102)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.251

3.5.7 The Risk Tolerance Questionnaire

The Risk Tolerance Questionnaire (RTQ) developed by Grable and Lytton (1999) was used to measure *Risk-Tolerance*. This measure is a subjective, multidimensional measure that focuses on risky financial scenarios and situations, used to derive an individual's level of *Risk-Tolerance*. It is a 13-item questionnaire that produces *Risk-Tolerance* scores for six domains: (a) the probability of gains, (b) the probability of losses, (c) the dollar[32] amount of potential gains, (d) the potential dollar loss through the assessment of guaranteed versus probable gambles, (e) minimum probability of success given a risky course of action, and (f) minimum returns given a risky course of action.

Grable and Lytton (1999) reported an internal consistency reliability coefficient of .75 for the full scale. Factor analysis results indicated that the instrument measures financial *Risk-Tolerance* on three constructs: (a) *Investment Risk*, (b) *Risk Comfort*

[32] For the purposes of this research, all references to "dollar" as a monetary unit were changed to "rand".

and Experience, and (c) *Speculative Risk*. However, in the initial validation study conducted by Grable and Lytton (1999) the coefficient alphas obtained for each of the three constructs were relatively low (.720, .502 and .443 respectively) and it was noted by the authors that the underlying dimensions "were not intended to be used as distinct measures" (Grable & Lytton, 1999, p. 177).

Correlation analysis between the RTQ and the Survey of Consumer Finances (a widely used proxy, consisting of one item for financial *Risk-Tolerance* in the United States of America) produced a coefficient of .54. Although moderate, the positive correlation may be an indication that the larger RTQ is measuring multiple dimensions of financial *Risk-Tolerance* that are not being measured by the SCF item (Grable & Lytton, 1999). A follow-up study conducted by Grable and Lytton in 2003 provided support for both the criterion-related and construct-related validity of the RTQ (Grable & Lytton, 2003).

3.5.7.1 Descriptive statistics and item analysis

The RTQ consist of 13 items. As proposed by the developers of the original instrument, item analysis was performed on the three underlying factors in order to demonstrate the dimensionality of the measure (see summary in table 3.24). The results were concerning as only one dimension, *Investment Risk*, obtained a satisfactory Cronbach's alpha of .635. The other two dimensions yielded values of .410 and .295, respectively, which implied that less than 50% of the variance in the subscale items could be attributed to true score/systematic variance and thus, more than 50% was due to error variance.

Table 3.24

The means, standard deviation and reliability statistics for the RTQ subscales

RTQ	Number of items	M	SD	α
Investment Risk	5	11.50	2.396	.635
Risk Comfort and Experience	5	10.35	1.971	.410
Speculative Risk	3	5.03	1.184	.295

However, as noted by the authors of the article, the underlying dimensions "were not intended to be used as distinct measures" (Grable & Lytton, 1999, p. 177) and therefore the item analysis was done merely to demonstrate the multidimensionality of the instrument. In light of this, an item analysis was conducted on the full scale. These results are summarised in table 3.25.

Table 3.25

The means, standard deviation and reliability statistics for the RTQ (full scale)

RTQ	Number of items	M	SD	α
RTQ	13	26.8585	4.17914	.676

The internal consistency reliability for the 13-item measure was .676, which is relatively close to the suggested 0.70 cut-off. The inter-item correlation matrix revealed that item RT03 correlated very low with the other items in the measure (-.069 to .135). The corrected item total correlation for this item was the lowest among the items at .102, as was the squared multiple correlation at .065. The results also suggested that the deletion of this item would result in an increase of the Cronbach's alpha from .676 to .694. Based on these findings, item RT03 was deleted and the item analysis was repeated for the reduced item instrument (see summary in table 3.26). Subsequently the inter-item correlation matrix revealed that item RT10 correlated very low with the other items in the measure (-.094 to .176). The corrected item total correlation for this item was the lowest among the items at .102, as was the squared multiple correlation at .069. The recalculated item statistics presented in table 3.26 indicated that if item RT10 was deleted the internal consistency reliability would increase to .701 (see table 3.27 for the recalculated statistics). Consequently this item was also removed and the original scale was reduced from 13 to 11 items. Grable and Lytton (1999) recommended that a *Risk-Tolerance* assessment index produce reliability coefficients in the range of .50 to .80 in order to be considered acceptable. The reported final internal consistency value (table 3.27) falls within the upper end of this range.

Table 3.26

The means, standard deviation and reliability statistics for the RTQ (12 item instrument)

RTQ	Number of items	M	SD	α
RTQ	12	25.0439	4.00282	.694

Table 3.27

The means, standard deviation and reliability statistics for the RTQ (11 item instrument)

RTQ	Number of items	M	SD	α
RTQ	11	23.4	3.925283	.701

3.5.7.2 Confirmatory factor analysis

3.5.7.2.1 Measurement model specification and data normality

SEM was used to perform CFA on the RTQ measurement model. In line with the original scale developers, Grable and Lytton (1999), CFA was performed on a single dimension, as the measure was primarily designed to reflect an individual's standing on the latent construct, *Risk-Tolerance* as a whole, and hence the computation of a total *Risk-Tolerance* score as opposed to subscale totals. Therefore, in the first instance the single latent factor measurement model was specified to consist of 11 observed variables (X's) and one unmeasured latent factor (ξ; i.e. *Risk-Tolerance*), with single-headed arrows from the ξ to the X's representing the proposed regression of the observed variables onto the latent factor.

Before CFA was performed, the variable type had to be considered. Most statistical methods for SEM assume that the data are observations of continuous variables. When multivariate datasets comprise of ordinal variables, they are typically treated and specified as continuous in order to overcome this problem. The use of Maximum Likelihood Estimation, in such an instance, is permissible to the extent that the scales consist of five or more scale points (Muthén & Kaplan, 1985). However, in this particular instance this approach may have yielded misleading results. Due to the varying nature of scale points, in terms of content and number of response categories (ranging from two to four in the RTQ), specifying the data as continuous and using Maximum Likelihood Estimation was not permissible. Hence, the data was treated as ordinal. When SEM is used to conduct CFA on ordinal data, the analysis of polychoric correlations and an asymptotic covariance matrix is required (Jöreskog, 2005). In this instance, Robust Diagonally Weighted Least Squares estimation (RDWLS) is a more appropriate estimation method. The univariate and multivariate normality of the indicator variables of the RTQ was not inspected before conducting the CFA. The a priori assumption is that the intervals between adjacent categories in ordinal variables are arbitrary and thus, it is not meaningful to screen the data for normality.

3.5.7.2.2 Evaluation of the measurement model

The measurement model is visually represented in figure 3.8.

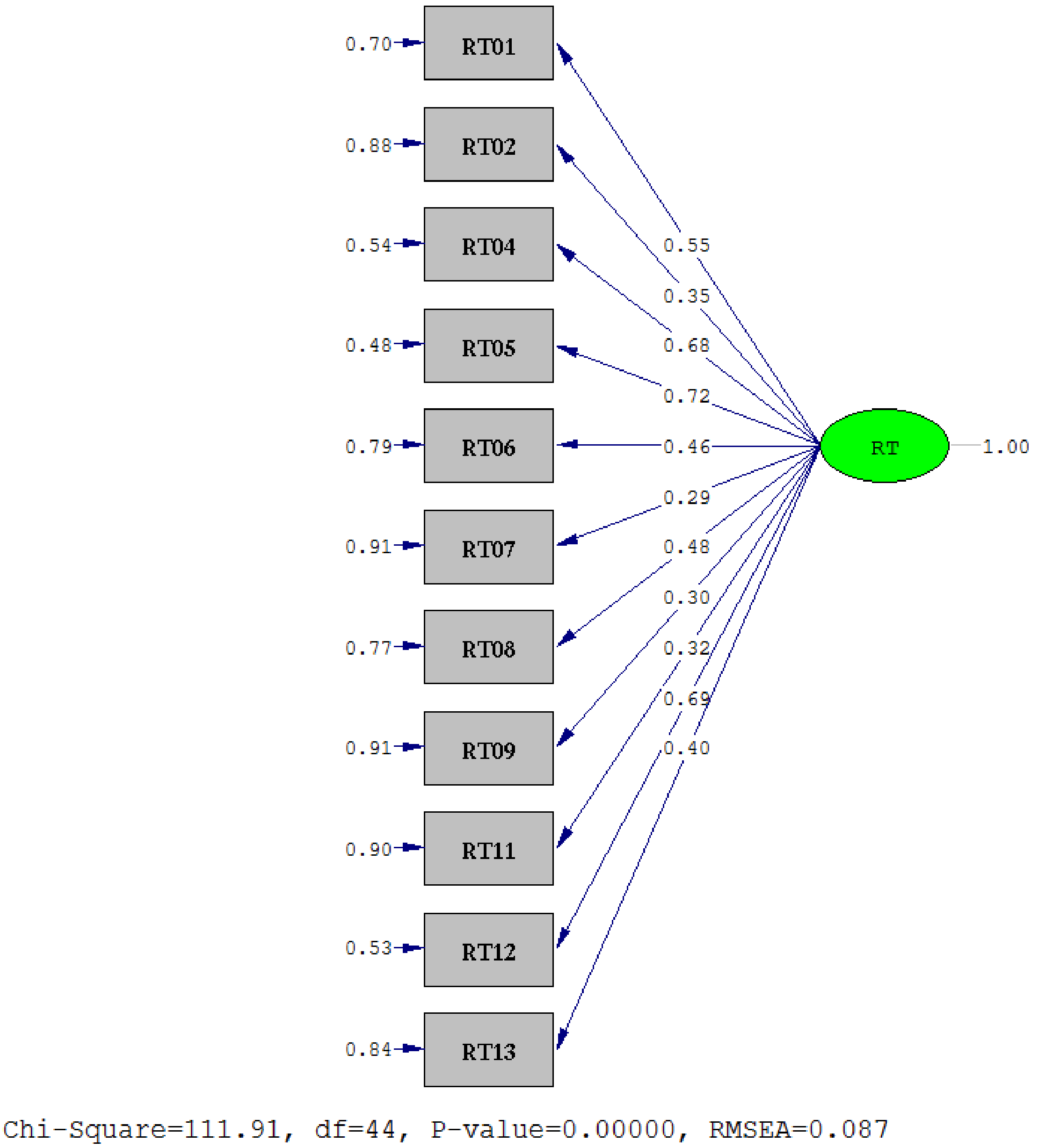


Figure 3.8. **Measurement model of the RTQ (standardised solution)**

Table 3.28 contains the results of the range of fit indices obtained for the CFA of the single factor measurement model. The exact fit null hypothesis of the measurement model in question was tested by means of the Satorra-Bentler scaled chi-square (S-B χ^2) statistic, which returned a value of 111.908 ($p = .000$). As a consequence, the exact fit null hypothesis was rejected ($p < .05$). The RMSEA of 0.0870, comparative fit index (CFI = .899) and non-normed fit index (NNFI = .874) did not meet the benchmark values of acceptable fit and thus, painted a negative picture of the fit of the model. The SRMR exceeded the < .08 cut-off level corroborating the inference of mediocre model fit. Of the 11 items, seven items obtained significant factor loadings above the .40 cut-off. The loadings ranged from .403 to .720.

Table 3.28

Goodness of fit statistics for the RTQ measurement model (11 item instrument)

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	210.585 (P = 0.0)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	111.908 (P = 0.000)
Degrees of Freedom	44
S-Bχ2/ df	2.54336364
Non-Normed Fit Index (NNFI)	0.874
Comparative Fit Index (CFI)	0.899
Root Mean Square Residual (RMR)	0.0914
Standardised RMR	0.0914
Root Mean Square Error of Approximation	0.0870
90 Percent Confidence Interval for RMSEA	(0.0672; 0.107)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.00166

The one-dimensional CFA yielded results that did not indicate good fit. It was decided to conduct a CFA on the three underlying dimensions of the measure i.e. *Investment Risk, Risk Comfort and Experience*, and *Speculative Risk*, in order to investigate the dimensionality of the measure. In this instance the model was specified to consist of 11 observed variables (X's) and three unmeasured latent factors (ξ's; i.e. *Investment Risk, Risk Comfort and Experience* and *Speculative Risk*), with single-headed arrows from the ξ's to the X's representing the proposed regression of the observed variables onto the three latent factors.

The measurement model in this instance represented the relationship between the *Investment Risk*, *Risk Comfort and Experience* and *Speculative Risk* constructs and its manifest indicators, and can be viewed in figure 3.9.

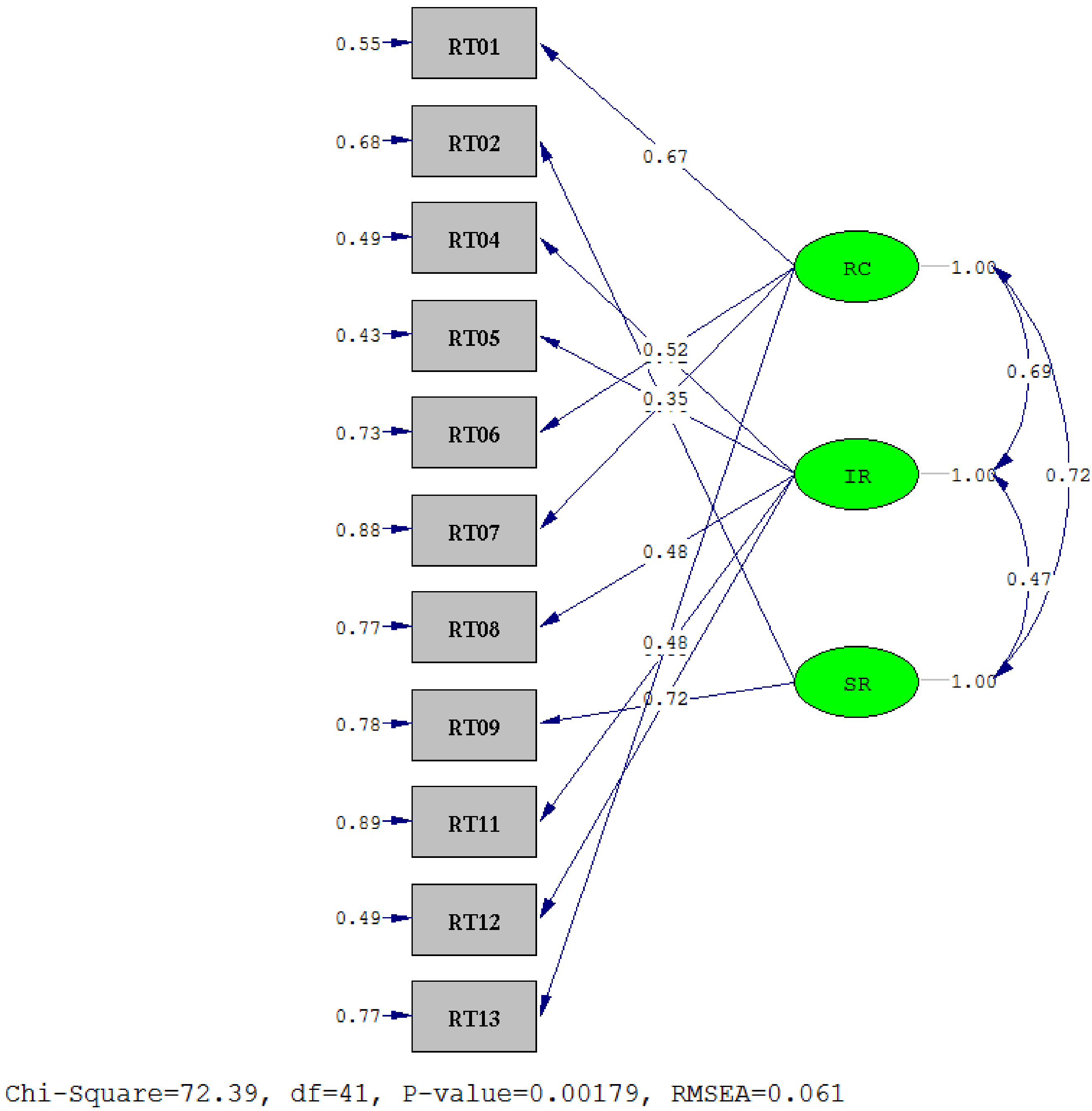


Figure 3.9. **Measurement model of the RTQ subscales (standardised solution)**

Table 3.29 contains the results of the range of fit indices for the three factor measurement model. The Satorra-Bentler scaled chi-square (S-B χ^2) statistic achieved a value of 72.394 (p = .00179). As a consequence, the exact fit null hypothesis was rejected ($p < .05$), thereby implying imperfect model fit. The RMSEA of 0.0613, comparative fit index (CFI = .954) and non-normed fit index (NNFI = .938) strongly suggested a well-fitting model, as did the standardised root mean square residual (SRMR = .0796). The probability of obtaining this sample RMSEA value under the assumption that the model fits closely in the population was sufficiently high at .201 not to discard the assumption as permissible (i.e. close fit was achieved). Of the 11 items, nine obtained significant factor loadings above the .40 cut-off. These loadings ranged from .467 to .757.

Table 3.29

Goodness of fit statistics for the RTQ measurement model (subscales)

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	134.787 (P = 0.00)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	72.394 (P = 0.00179)
Degrees of Freedom	41
S-Bχ2/ df	1.7657
Non-Normed Fit Index (NNFI)	0.938
Comparative Fit Index (CFI)	0.954
Root Mean Square Residual (RMR)	0.0796
Standardised RMR	0.0796
Root Mean Square Error of Approximation	0.0613
90 Percent Confidence Interval for RMSEA	(0.0371; 0.0841)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.201

As was argued, the RTQ was originally developed to measure a general *Risk-Tolerance* factor. However, factor analytic results in the original validation study of the measure (Grable & Lytton, 1999) revealed that the scale also measures three specific underlying factors reflecting different domains of *Risk-Tolerance*. Consequently, the data was fitted separately to two models with one and three factors, respectively. Factor analytic results in this research produced greater support for the three-factor model. However, the ideal would have been to successfully fit a model that could reflect a dominant factor whilst simultaneously capturing remaining common variance across items in the three underlying factors. Towards this end, an attempt was made to fit the data to a bifactor model, which would have provided the best account of the underlying factor structure of the RTQ. Confirmatory bifactor modelling provides a method for evaluating competing structural models in explaining the latent dimensions of an instrument (Canivez, in press). In this instance the bifactor model was specified by modelling all indicator variables onto both a single common latent factor, i.e. *Risk-Tolerance*, and the specific latent dimensional factor to which it is theoretically related. Therefore, each indicator had one path from a dimensional factor and one from the general factor, i.e. *Risk-Tolerance*. Bifactor modelling accommodates the proposed hierarchical structure of the RTQ by allowing the research to retain the idea of a single common construct whilst acknowledging the multidimensionality of the measure. Unfortunately, when the model was fitted the solution did not converge and was rendered inadmissible.

Consequently, even though the three-factor structure displayed good fit in comparison with the unidimensional factor structure, a decision was made to include *Risk-Tolerance* as a single latent variable in the subsequent analyses. This was done in attempt to protect the original design intention of the scale, which was to produce a single *Risk-Tolerance* score.

Further to this, consideration was also given to the formation of item parcels prior to the evaluation of the measurement and structural models, which will be discussed in the subsequent chapter. According to Little, Cunningham, Shahar, and Widaman (2002) the law of large numbers typically holds for indicators of constructs and suggests that more items are better than fewer items in estimating a construct centroid. Moreover, when more items are combined and aggregated into parcels non-normal distributions become more normally distributed, and scale intervals increase in number and effectively become both smaller and more equal with regard to distances between points (Little et al., 2002). When fewer items are included, models are more likely to be under identified and may fail to converge. Essentially, models using parcels containing a greater number of items are more desirable as it may improve fit indices and produce a more comprehensive representation of a construct (Little et al., 2002).

For the reasons stated above, a decision against the inclusion of a multidimensional *Risk-Tolerance* and *Sensation Seeking* latent variable was made, as it would have implications for the success with which the latent variables were operationalised in the measurement and structural models. More specifically, if item parcels had to be formed for *Sensation Seeking,* it would be possible to combine pairs of items representing each of the four identified dimensions of the BSSS. This would mean that the resultant composites as indicators of *Sensation Seeking* would consist of only two items. This would also be the case for the third dimension (*Speculative Risk*) of the RTQ, which after the removal of poor items consisted of only two items. The inclusion of only two items in the item parcels may have led to the attenuation of the resulting fit indices.

3.6 Conclusion Regarding the Psychometric Integrity of the Measurement Instruments

The item analyses conducted on the range of scales and subscales used in this study achieved the results presented in table 3.30.

Table 3.30

A summary of the reliability results of the Client Risk-Tolerance Questionnaire latent variable scales/subscales

Scale	Sample size	Number of items	Mean	Standard deviation	Cronbach alpha	Number of items deleted
Extraversion	205	4	13.39	3.221	.729	0
Agreeableness	205	4	15.30	2.689	.689	0
Neuroticism	205	4	10.55	2.758	.548	0
Conscientiousness	205	4	15.34	2.785	.588	0
Intellect/ Imagination	205	4	14.23	2.842	.650	0
BSSS	205	8	24.64	5.912	.764	0
ESM	205	10	37.44	4.611	.737	0
ESC	205	9	37.72	4.603	.715	1
DGI	205	7	30.98	3.834	.776	0
RTQ	205	11	23.40	3.925	.701	2

The item analyses results revealed that eight out of the ten scales/subscales returned Cronbach's alpha reliability coefficients above the critical cut-off values[33] set for the current study. It is acknowledged that two of the subscales comprising the Mini-IPIP, i.e. *Neuroticism* and *Conscientiousness*, yielded concerning results (alpha < .60). Furthermore, completely standardised factor loadings below the cut-off value (.40) were obtained for three items in these two subscales. This included items IPIP09 (*Neuroticism*), IPIP13 (*Conscientiousness*) and IPIP19 (*Neuroticism*) with loadings of .259, .350 and .209, respectively. However, deleting items from these scales were not an option as the subscales already comprised of a limited number of items (m = 4), and no significant increase in the alphas would be incurred from doing so.

The item analysis conducted on the underlying dimensions of the RTQ returned poor reliability coefficients for two of the dimensions (.410 and .295). As mentioned, it needs to be taken into account that the original design intention of the measure was to construct a uni-dimensional *Risk-Tolerance* construct, and hence *Risk-Tolerance* was included in the structural model as a single latent variable. The reliability coefficient (.701) obtained in the second instance, with 11 retained items representing the scores on the *Risk-Tolerance* latent variable, mitigated the unfavourable picture that emerged from the item analysis performed on the three sub-dimensions. Overall, it could be concluded that sufficient evidence was produced to conclude satisfactory internal consistency of most of the scales/subscales utilised in this study.

The primary purpose of the item and dimensionality analysis was to detect and remove poor items. Only three items from the composite questionnaire, containing all scales and subscales intended for this study, were deleted and excluded from further analyses. The results suggested the removal of one item, ER12, from the *Emotional Self-Control* subscale. During the EFA only one item, ER12 loaded onto the third extracted factor, resulting in the decision to delete this item from the final item pool (coupled with the fact that the item analysis results flagged this as a possible

[33] Each measured subscale was considered acceptable if the Cronbach's alpha value exceeded .70. However, due to the fact that the coefficient of internal consistency is attenuated by a limited number of scale items, the acceptable value was set at .60 for the Mini-IPIP with m = 4 per subscale.

problematic item). Two items, RT03 and RT10, were removed from the RTQ. The *Emotional Self-Control* subscale was therefore reduced from 10 to nine items and the RTQ was reduced from 13 to 11 items.

The CFA results for the five factor Mini-IPIP scale, *Emotional Self-Management* subscale and DGI ranged from adequate to good. For the *Emotional Self-Control* subscale, dimensionality analyses were performed to determine the underlying factor structure. The results demonstrated that the *Emotional Self-Control* subscale failed to pass the uni-dimensionality assumption as was originally hypothesised. Initially an unrestricted EFA led to the extraction of three factors. However, only one item loaded onto the third factor and was consequently deleted. A two-factor solution was successfully forced. To strengthen the psychometric support of the scale, CFA analysis were conducted once more on the derived two factor structure from the EFA results. In this instance, it was concluded that the two-factor model provided a better account of the structure of the instrument in this particular sample. Initial inspection of the item content failed to produce meaningful underlying theoretical themes. A closer inspection of the item wording, however, pointed towards the presence of possible method bias. The items loading on the derived two-factor structure could largely be grouped into positive and negatively worded units.

Even though the results of the three dimensional CFA of the RTQ supported good model fit, the one-dimensional analyses did not paint the same positive picture and mediocre fit was concluded. This was, however, anticipated as the measure consisted of variable scales points with as low as two response categories per item, the highest being four. Statistically, scales with a smaller number of response categories, generally two to four, are commonly expected to yield scores that are lower in reliability, validity and discriminatory power compared to those with five or more response categories.

The uni-dimensional BSSS produced undesirable results. Based on the fact that the BSSS was founded on Zuckerman's Sensation Seeking Scale Form V (SSS-V) and thus reflected four dimensions, it was decided to conduct a CFA on the four underlying dimensions. The range of fit indices produced satisfactory results and statistically, perfect model fit was concluded.

It is undeniable that there exists opportunity for improvement with regards to the deficient reliability and validity of selected measures. It is acknowledged that poor reliability and validity in measurement could jeopardise the subsequent results obtained through SEM. With specific reference to the low reliability scores attained by the *Neuroticism* and *Conscientiousness* subscales, and the mediocre CFA results produced by the RTQ (for the one factor model) – the potential detrimental effects in subsequent analyses and accuracy of interpretation was noted.

That being said, the basket of evidence provided at least some justification for the use of these scales in the subsequent analyses to represent the latent variables they were earmarked to reflect.

CHAPTER 4
RESULTS

4.1 Introduction

Chapter 4 reports on the empirical evidence attained in this research. The chapter commences with a discussion of the sample. This includes the manner in which the demographic and socioeconomic information of the respondents were elicited, followed by an in-depth discussion of the sample characteristics. The measurement model is presented and evaluated in terms of the statistical significance and magnitude of its parameter estimates. On the condition that the operationalisation of the latent variables were successful, as is the case in the current research study, the structural model fit and adequacy of the structural model parameter estimates were evaluated via structural equation modelling (SEM) in LISREL. In addition, to explore whether *Gender, Age, Income* and *Education* acted as moderators in the relationships between the various personality and emotion regulation variables and *Risk-Tolerance*, a series of moderated multiple regression analyses was conducted via SPSS.

4.2 Sample

4.2.1 Measurement of demographic and socioeconomic information

The demographic and socioeconomic information included *Gender, Age, Income* and *Education. Gender, Age, Income* and *Education* were determined by means of four short questions included in the *Client Risk-Tolerance* Questionnaire. *Gender* was measured on a 2-point scale, where 1 = male and 2 = female. *Age* was collected as a continuous numerical variable by asking respondents to state their current age.

Income was measured based on the results of the household income and expenditure patterns in South Africa in 2011, as reported by *The Bureau of Market Research of the University of South Africa* (Masemola, Van Aardt, & Coetzee, 2012). It was measured on a seven-point scale with 1 representing the lowest score, i.e. Poor (R0-R54344 per annum) and 7 representing the highest score, i.e. Affluent (R1 329 845+ per annum).

The question relating to *Education* level was derived from the level descriptors for the South African National Qualifications Framework. The framework is based on 10 categorical levels that refer to a series of levels of learning achievement arranged in ascending order from 1 to 10. Table 4.1 provides an indication of the level descriptors associated with each of the 10 levels.

Table 4.1

NQF level descriptors

	NQF Level
10	*Doctorate*
9	*Master's Degree*
8	*Honour's Degree*
	Postgraduate Diploma
7	*Bachelor's Degree*
	Advanced Diploma
6	*Diploma and Advanced Certificates*
5	*Higher Certificates and Advanced National (Vocational) Certificate*
4	*Grade 12 (National Senior Certificate)*
3	*Grade 11*
2	*Grade 10*
1	*Grade 9*

(Department of Higher Education and Training, 2013)

4.2.2 Sample characteristics

A total of 205 clients seeking, or already receiving investment advice from various financial institutions in South Africa, completed the composite questionnaire that was developed and distributed for this research study. The sample characteristics relating to *Age, Gender, Income* and *Education* are presented in table 4.2.

Table 4.2

Demographic and socioeconomic sample characteristics

Gender		
Category	Frequency	Percentage (%)
Male	118	58.1
Female	85	41.9
Age		
Category	Frequency	Percentage (%)
20-29	99	48.8
30-39	28	13.8
40-49	19	9.4
50-59	20	9.9
60-69	30	14.8
70-79	6	3.0
80-89	1	0.5
Education		
Category	Frequency	Percentage (%)
Grade 9	0	0.0
Grade 10	1	0.5
Grade 11	3	1.5
Grade 12 (National Senior Certificate)	24	11.7
Higher Certificate/ Advanced National (Vocational) Certificate	8	3.9
Diploma/ Advanced Certificate	21	10.2
Bachelor’s Degree/ Advanced Diploma	66	32.2
Honour’s Degree/ Postgraduate Diploma	60	29.3
Master’s Degree	17	8.3
Doctorate	5	2.4
Annual Income		
Category	Frequency	Percentage (%)
R0-R54 344	10	4.9
R54 345-R151 727	35	17.2
R151 728-R363 930	76	37.3
R363 931-R631 120	51	25.0
R631 121-R863 906	12	5.9
R863 907-R1 329 844	13	6.4
R1 329 845+	7	3.4

From the sample profile presented in table 4.2, it is evident that the *Gender* distribution was skewed towards males in that 58.1% of the respondents were male, against 41.9% female respondents. *Age* ranged from 22 to 82 years, with a mean of 39.93 and a standard deviation of 16.33. *Age* was collected as a continuous numerical variable. Using SPSS Version 22.0 (IBM Corp, 2013), a categorical variable was created via the recoding function. Consequently data was reorganised into seven collapsed categories. The results revealed that the distribution was positively skewed (.800), with a clear majority of the sample consisting of individuals aged 20 to 29 (48.3%), whilst only one individual placed into the uppermost category, ages 80 to 89. Furthermore, the *Education* distribution was negatively skewed (-.733) with a larger proportion of the sample having obtained a tertiary qualification. Almost a third of the sample (32.2%) completed a Bachelor's degree or Advanced Diploma and 29.3% held an Honour's degree or Postgraduate Diploma. Most individuals indicated an annual gross income before taxes of R151 728 - R363 930 (37.3%), followed by an income of R363 931 - R631 120 (25%).

4.3 Item Parcels

Item parcels were constructed for each latent variable during the assessment of the measurement and structural models. When using LISREL to assess the measurement and structural models, the most effective solution would have been to execute the operationalisation of the latent variables through the use of individual items comprising the scales or subscales in the model. This, however, would have led to an extensively comprehensive model in which a large number of parameters would have to be estimated. Item parcels were used instead, which sufficiently reduced the number of parameters to be estimated.

According to Hall, Snell, and Foust (1999) item parcels as composite-level indicators, as opposed to individual items, tends to be more reliable and normally distributed. It has also been suggested that as the number of indicators per latent factor increases, there are associated decreases in the value of a number of commonly used fit indices (Williams & Holahan, 1994 as cited in Boers, 2014). According to Hoyle (2014) parcel-level models improve model fit by creating more continuously measured units. Compared with item-level data, models that are based on parcelled data contain less sources of contamination that may contribute to overall lack of model fit. Parcelled data are more parsimonious, have a lower potential for residuals to be correlated or dual loadings to emerge (as fewer indicators are used and unique variances are smaller), and lead to reductions in various sources of sampling error (Little et al., 2002). In light of the aforementioned, it was decided to construct a minimum of two parcels of indicator variables per latent factor in the model. The results of the item-, dimensionality-, and confirmatory factor analyses justified the formation of item parcels for each of the latent variables included in the structural model.

Two item parcels were formed for the Brief Sensation Seeking Scale (BSSS) by grouping the even and uneven numbered items together. Similarly, the Delaying Gratification Inventory (DGI) item parcels were formed by grouping the even and uneven numbered items together. More specifically the means of the even and uneven numbered items of each scale were computed in SPSS.

The Mini-IPIP's parcels were formed by grouping the items according to the five different personality subscales (i.e. *Extraversion, Openness to Experience*[34]*, Conscientiousness, Agreeableness* and *Neuroticism*). For each of the five constructs two item parcels with randomly selected items were formed. Three item parcels were formed for *Emotional Self-Management,* by randomly selecting items from the *Emotional Self-Management* item pool. *Emotional Self-Control* was represented by two item parcels that were formed by taking the mean of the items loading onto the first (positively phrased) and second (negatively phrased) factors extracted during the exploratory factor analyses (EFA)[35]. Due to the variable nature of the scale points of the Risk Tolerance Questionnaire (RTQ), the *Risk-Tolerance* latent variable was represented by two item parcels that were formed by carefully allocating items into two groups of (more or less) equal summated scale points.

[34] Referred to as Intellect/Imagination in the Mini-IPIP measurement instrument.
[35] This approach was followed as there is research evidence to suggest that the uni-dimensionality assumption of the parcels should not be violated. Therefore the EFA results (where available) were utilised to construct parcels.

The item parcel data set was subsequently imported into PRELIS to evaluate the multivariate normality of the item parcel distributions. The parcels were treated as continuous variables.

4.4 Client Risk-Tolerance Measurement Model

The measurement model schematically represents the relationship between the *Client Risk-Tolerance* latent variables and its corresponding item parcel indicator variables. The aim of fitting the measurement model was to determine the validity and reliability of the measures used to represent the constructs of interest (Diamantopoulos & Siguaw, 2000).

4.4.1 Confirmatory factor analysis

The substantive research hypothesis was tested by fitting the comprehensive LISREL model. The comprehensive LISREL model encompasses a structural model, an endogenous measurement model and an exogenous measurement model. The endogenous and exogenous measurement models define the nature of the hypothesised relationships between the latent variables and the indicator variables that represent them. Structural model fit indices could only be interpreted unambiguously for or against the fitted structural model if it were proven that the indicator variables used to operationalise the latent variables when fitting the structural model, successfully reflected the latent variables they were tasked to represent (Diamantopoulos & Siguaw, 2000). Therefore, the measurement model fit needed to be evaluated prior to fitting the structural model. As opposed to fitting two separate endogenous and exogenous measurement models, the two models were combined and fitted as a single exogenous measurement model (Swart, 2011).

The covariance matrix was analysed during the fitting of the measurement model. Robust maximum likelihood estimation (RML) was used as the null hypothesis for multivariate normality in the observed data was rejected. LISREL 8.8 (Du Toit & Du Toit, 2001) was used to perform the CFA.

The measurement hypothesis that the measurement model provided a valid description of the process that brought about the observed covariance matrix, was evaluated (Hair et al., 2006). If the measurement hypothesis was taken to mean that the measurement model provided a perfect account of the manner in which the latent variables manifest themselves in the indicator variables, the measurement hypothesis translated into the following exact fit null hypothesis:

$$H_{01a}: \text{RMSEA} = 0$$
$$H_{a1a}: \text{RMSEA} > 0$$

However, it is somewhat idealistic to assume that the measurement model would provide a perfect account of the manner in which the latent variables manifest themselves in the indicator variables and therefore it was expected to reject the null hypothesis (H_{01a}). If the measurement hypothesis was taken to mean that the measurement model only provided an approximate description of the process that produced the observed covariance matrix, the measurement hypothesis translated into the following close fit null hypothesis:

$$H_{01b}: \text{RMSEA} \leq 0.05$$
$$H_{a1b}: \text{RMSEA} > 0.05$$

4.4.2 Interpretation of measurement model fit and parameter estimates

Measurement model fit was interpreted by inspecting the range of indices provided by LISREL (Diamantopoulos & Siguaw, 2000). Further consideration was given to the magnitude and distribution of the standardised residuals, the magnitude of model modification indices calculated for Λ^X, Θ_ε and Θ_δ, the model parameter estimates and the squared multiple correlations (R^2) for the indicator variables. Residuals represent a measure of the strength of the difference between elements of the observed and reproduced covariance matrices. If a sample is large enough, the standardised residuals can be interpreted as z-scores, i.e. in terms of standard deviation units from the mean (Diamantopoulos & Siguaw, 2000). Standardised residuals are considered positively or negatively large, i.e. the observed frequency is greater than the reproduced frequency, if they exceed the absolute value of + 2.58 or fall below -2.58 (Diamantopoulos & Siguaw, 2000). Good model fit is indicated by residuals that are distributed approximately symmetrical around zero. Positive residuals suggest underestimation and imply the need for additional explanatory paths. Negative residuals indicate overestimation and suggest the need to reduce the number of explanatory paths.

Modification indices indicate the extent to which the value of the chi-square (χ^2) fit statistic will decrease if a currently fixed parameter in the model is freed. Large modification index values indicate the measurement model parameters that, if set free, would improve the fit of the model. A large number of large and significant modification index values comment negatively on the fit of the model and suggests that numerous possibilities exist to improve the fit of the proposed model.

The completely standardised factor loadings reflect the average change, expressed in standard deviation units, in the indicator variables associated with one standard deviation change in the latent variables to which they have been linked, given that the effect of all other variables are held constant (Diamantopoulos & Siguaw, 2000). The factor loading estimates were considered to be satisfactory if the completely standardised factor loading estimates exceeded a stringent cut-off of .71 (Hair et al., 2006). The squared multiple correlations (R^2) calculated and interpreted for each of the indicators signify the proportion of the variance in a specific indicator that is explained by its underlying latent variable. High R^2 values are preferred.

Operationalisation of the latent variables that encompass the structural model will be considered successful if (a) the measurement model shows close fit, (b) the completely standardised factor loading estimates are statistically significant ($p < .05$) and exceed the stringent 0.71 cut-off (Hair et al., 2006), (c) the measurement error variances for all items are statistically significant and small, and (d) reasonably large R^2 values ($R^2 \geq .25$) for all items are obtained (Van Heerden, 2013). If at least reasonable fit was obtained for the *Client Risk-Tolerance* measurement model and if the parameter estimates satisfied the stipulated conditions, the *Client Risk-Tolerance* structural model could be tested by fitting the reduced structural model with LISREL.

4.4.3 Discriminant validity

The ten latent variables represented in the hypothesised *Client Risk-Tolerance* structural model were regarded as qualitatively distinct, yet causally related constructs. Due to the causal relations hypothesised in the model, some degree of correlation was expected as each measure of a construct could be expected to be related to a measure of another construct. However, the ideal would be for the latent variables comprising the study to be measured in such a way that the measurement reflects essentially a single construct, and as such high levels of discriminant validity was sought. That is, the correlations between the latent variables had to be sufficiently low to conclude that the latent variables were successfully operationalised as distinct constructs. Discriminant validity would be indicated if all Φ_{ij} estimates were smaller than .90. This was investigated by inspecting the Φ matrix.

4.5 Evaluating the Fit of the Client Risk-Tolerance Measurement Model

4.5.1 Screening the data

LISREL 8.80 (Jöreskog & Sörbom, 2002) was used to perform the CFA on the measurement model. The data failed to satisfy the multivariate normality assumption (skewness and kurtosis: 63.402, $p < .05$). Thus, RML estimation was employed to derive the model parameter estimates.

Table 4.3

Test of multivariate normality of the Client Risk-Tolerance measurement model

	Skewness			**Kurtosis**		**Skewness and Kurtosis**	
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
49.201	6.295	0.000	419.051	4.876	0.000	**63.402**	**0.000**

4.5.2 Measurement model fit

The aim of the CFA was to determine whether the operationalisation of the item parcels in terms of its latent variables was successful. Good model fit could be concluded if close fit was evident, the item parcels loaded statistically significantly onto the latent variables of interest, and if the completely standardised factor loadings exceeded a stringent cut-off of .71 (Hair et al., 2006).

When the *Client Risk-Tolerance* measurement model was originally fitted to the data, the solution converged but was rendered inadmissible. The preliminary LISREL output produced the following warning message in the unstandardised solution: "W_A_R_N_I_N_G: *PHI is not positive definite*". This pointed towards the presence of multicollinearity, i.e. two predictor variables were deemed to be too highly correlated. Upon closer inspection of the completely standardised phi matrix, an inter-correlation coefficient (1.044) between *Emotional Self-Management* and *Emotional Self-Control* beyond the allowable limit (i.e. 1) was noted. This further underscored the finding that the solution was inadmissible, and could not be reported. Based on this result it was decided to remove the *Emotional Self-Control* construct from the *Client Risk-Tolerance* structural model. Hence, this variable was not included in any further analyses conducted in this study. The reasoning for this decision was twofold. First, during the investigation of the psychometric properties of the individual measurement scales, the results for the *Emotional Self-Control* measure was not very convincing, as the presence of some method bias were uncovered. Secondly, although *Emotional Self-Control* and *Emotional Self-Management* are both sub-dimensions of an overarching construct (emotional intelligence as measured with the Genos EI, Gignac, 2010) these two sub-dimensions should still show discriminant validity to justify their inclusion as two separate dimensions of emotional intelligence. This seemed to not be the case in the current study. It was, therefore, concluded that *Emotional Self-Control* does not make an empirically unique contribution to the model and does not represent phenomena of interest that is not already captured in the model. Consequently, a reduced *Client Risk-Tolerance* measurement model with nine latent variables was fitted and successfully converged. The measurement model is graphically depicted in figure 4.1.

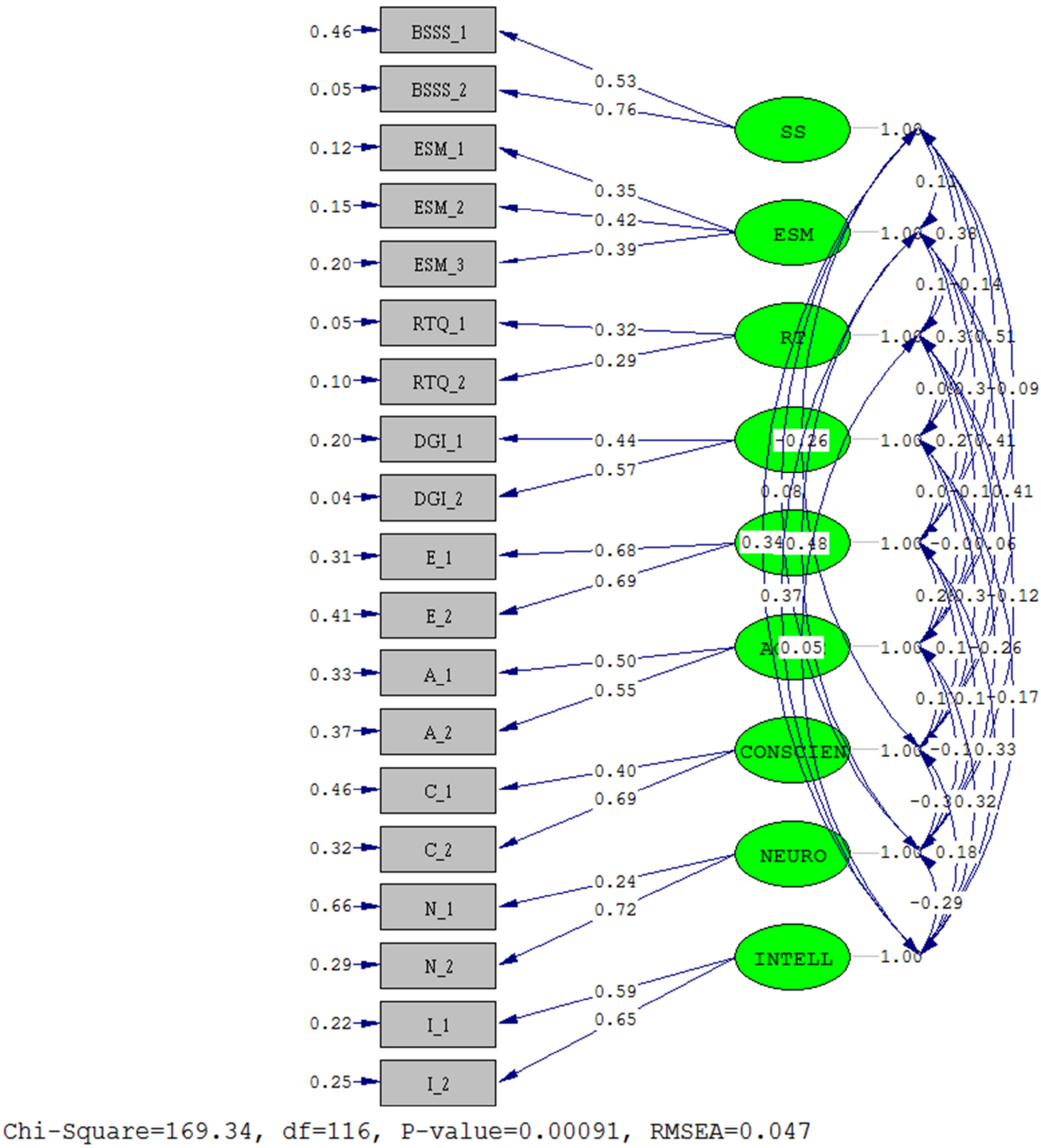


Figure 4.1. **Fitted measurement model (standardised solution)**

According to Diamantopoulos and Siguaw (2000) the purpose of assessing the overall fit of the model is to determine the degree to which the model as a whole is consistent with the empirical data at hand. A wide range of goodness-of-fit-indices (GOF) exists to evaluate model fit. It is important to take cognisance of the fact that none of the indices are unequivocally superior to the rest in all circumstances. The selected GOF indices obtained for the measurement model are summarised in table 4.4.

Table 4.4

Goodness of fit statistics for the Client Risk-Tolerance measurement model CFA

Goodness of Fit Statistics	
Normal Theory Weighted Least Squares Chi-Square	174.699 (P = 0.00)
Satorra-Bentler Scaled Chi-Square (S-Bχ2)	169.342 (P = 0.000913)
Degrees of Freedom	116
S-Bχ2/ df	1.4598
Non-Normed Fit Index (NNFI)	0.937
Comparative Fit Index (CFI)	0.957
Root Mean Square Residual (RMR)	0.0347
Standardised RMR	0.0591
Root Mean Square Error of Approximation	0.0475
90 Percent Confidence Interval for RMSEA	(0.0309; 0.0624)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.592

The measurement model achieved a Satorra-Bentler Chi-square value of 169.342 (p = 0.000913). The null hypothesis of exact fit, i.e. the assumption that the model fits perfectly in the population, was consequently rejected ($p < .05$).

To assess whether the measurement model closely approximated the psychological processes that underlie the *Client Risk-Tolerance* measurement model, the P-value for the test of close fit (RMSEA < .05) was considered. For this model, table 4.4 shows that the close fit null hypothesis should not be rejected (.592; $p > .05$) and it was concluded that the model displayed close fit in the parameter. The RMSEA value of .0475 corroborated this inference.

The comparative fit indices (CFI) contrast how much better the model of interest reproduced the observed covariance matrix than an alternative model, which is usually the null or independence model. Values that approach unity (1.00) indicate acceptable fit. However, Hair et al. (2006) suggested that values above .95 provide a strong indication of a well-fitting model. Diamantopoulos and Siguaw (2000) suggested a slightly lower benchmark value of .90. The fit indices presented in table 4.4 reflect the non-normed fit index (NNFI = .937) and the comparative fit index (CFI = .957). It was concluded that these index values satisfied the criteria. Overall, there was sufficient indication of satisfactory comparative fit relative to the independent model.

The standardised root mean residual (SRMR) is considered as a summary measure of standardised residuals, which represent the average difference between the elements of the sample covariance matrix and the fitted covariance matrix. Lower SRMR-values indicate better fit and higher values indicate worse fit. If the model fit is good, the fitted residuals should be small in comparison to the enormity of the elements (Diamantopoulos & Siguaw, 2000). SRMR-values that are smaller than .08 are indicative of an acceptable fit in this instance, where the number of observed variables is larger than 12 and smaller than 30 (Hair et al., 2006). The model achieved a SRMR of .0591, which fell comfortably below the .08 cut-off value, once again indicating good model fit.

In conclusion, the results appeared to suggest that good measurement model fit was achieved based on a selection of the GOF indices. In the subsequent sections, the standardised residuals, modification indices and parameter estimates are reported, to provide additional information to further inform the final conclusion regarding the measurement model fit.

4.5.3 Examination of the measurement model standardised residuals and modification indices

The examination of the standardised residuals and the modification indices provide relevant diagnostic information that can be used for the modification of the model with the purpose of improving the model's fit (Diamantopoulos & Siguaw, 2000). The standardised residuals and modification indices calculated for the lambda-X and theta-delta, comment on the quality of the measurement model (Prinsloo, 2011). When a limited number of ways exist to improve the model fit, it comments positively on the model fit.

4.5.3.1 Standardised residuals

Table 4.5 provides a summary of the standardised residuals and indicates that five of standardised residuals obtained values greater than 2.58, and five of the standardised residuals obtained values smaller than -2.58. The 10 large residuals constitute 5.26%[36] of the total number of unique variance and covariance terms in the observed variance-covariance matrix. Hence, approximately 5% of the observed variances and covariances were poorly, or inaccurately estimated from the measurement model parameter estimates. This can be regarded as acceptable and relatively small, though not ideal.

Table 4.5

Summary statistics for the Client Risk-Tolerance measurement model standardised residuals

Description	**Values**
Smallest Standardised Residual	-10.439
Median Standardised Residual	0.000
Largest Standardised Residual	3.061
Largest Negative Standardised Residuals	
Residual for RTQ_2 and BSSS_2	-3.261
Residual for DGI_2 and RTQ_1	-10.439
Residual for A_1 and ESM_3	-3.159
Residual for N_1 and BSSS_1	-2.811
Residual for N_1 and BSSS_2	-2.977
Largest Positive Standardised Residuals	
Residual for A_2 and E_2	3.061
Residual for C_2 and BSSS_1	2.690
Residual for C_2 and DGI_1	2.622
Residual for N_1 and C_1	2.967
Residual for I_2 and C_2	2.582

Note: ESM_3 = Emotional Self-Management; RTQ_1 & RTQ_2 = Risk-Tolerance; DGI_1 & DGI_2 = Delay of Gratification; BSSS_1 & BSSS_2 = Brief Sensation Seeking Scale; E_2 = Extraversion; A_1 & A_2 = Agreeableness; N_1 = Neuroticism; C_1 & C_2 = Conscientiousness; I_2 = Openness to Experience.

[36] The residual matrix for the model contains ([19x20]/2) = 190 elements.

A stem-and-leaf plot allows for the collective investigation of all standardised residuals (Diamantopoulos & Siguaw, 2000). The stem-and-leaf plot of a good fitting model would be characterised by residuals that are distributed approximately symmetrically around zero. As is evident from figure 4.2, the distribution of the standardised residuals appeared slightly more negatively skewed, i.e. the stem-and-leaf plot contains an excess of residuals on the negative side. This suggested that the observed variance and covariance terms in the observed covariance matrix were typically overestimated by the derived model parameter estimates. Deleting paths from the model could rectify this problem.

```
-10|4
- 9|
- 8|
- 7|
- 6|
- 5|
- 4|
- 3|320
- 2|8540
- 1|9988877666554333332222111100
- 0|9999999888877776666555544444433222111100000000000000000000000000000000000000
  0|11111111223334445555555555555666677777788899
  1|000011122223445566668899
  2|01122335555667
  3|01
```

***Figure 4.2*. Stem-and-leaf plot of the Client Risk-Tolerance measurement model standardised residuals**

The Q-plot of the measurement model, depicted in figure 4.3, plots the standardised residuals (horizontal axis) against the quintiles of the normal distribution (Diamantopoulos & Siguaw, 2000). When interpreting the Q-plot, it is crucial to determine the extent to which the data points fall on a 45-degree reference line. Data that falls on the 45-degree reference line is indicative of good model fit. In contrast, data points that deviate from the 45-degree reference line indicate a model fit that is less than satisfactory (Jöreskog & Sörbom, 1996b).

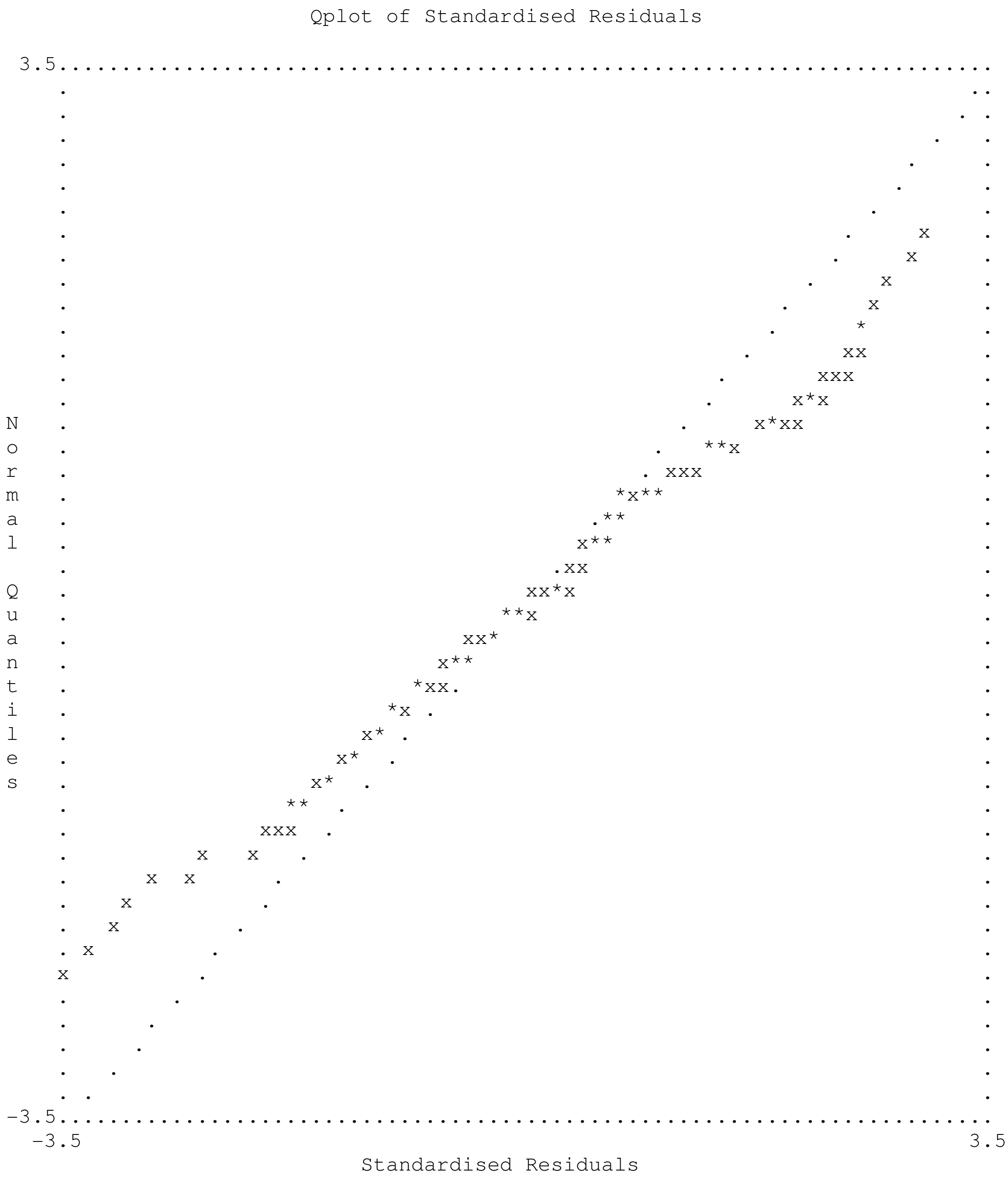


Figure 4.3. **Q-plot for the measurement model standardised residuals**

From figure 4.3 it is evident that the data points swivel away from the 45-degree reference line. The Q-plot does however indicate good to reasonable model fit, as the standardised residuals tend to deviate from this line mostly in the upper and lower regions on the X-axis. These findings corroborate the results reported in figure

4.2 and table 4.5, where there were both large positive and large negative standardised residuals, but where the negative standardised residuals were more prevalent.

4.5.3.2 Modification indices

The design intention of each item parcel was to reflect a respondent's standing on a specific latent variable. It was acknowledged that no item parcel would be a perfectly valid measure of the latent variable it was assigned to reflect. However, the item parcels were nonetheless created with the intention that the systematic measurement error component of each item parcel does not have a common source. The intention was therefore that the measurement error terms should be uncorrelated (Prinsloo, 2011). The measurement model in this instance reflected these intentions. In Λ_X each item parcel was allowed to load onto one latent variable only, with all other loadings fixed to zero. According to Jöreskog and Sörbom (2002) modification indices show the extent to which the X^2 fit statistics decrease if a currently fixed parameter in the model is freed and the model fit is re-estimated. Modification indices with values that exceed 6.64 are considered large and suggest currently fixed parameters that if set free, would significantly improve model fit ($p < .01$).

In this study, the evaluation of the modification indices were not so much focussed on identifying possible ways of actually modifying the measurement model. Instead, investigation thereof served the purpose of further evaluating the fit of the measurement model. If only a limited number of ways exist to improve the fit of the model, it commented favourably on the fit of the current model. In contrast to this, a large number of large modification index values would comment negatively on the fit of the model. The modification indices calculated for the lambda-X and theta-delta matrices are presented in table 4.6 and table 4.7.

Table 4.6

Measurement model modification indices for lambda-X

	SS	ESM	RT	DG	EXTRA	AGREE
BSSS_1	- -	**7.923**	2.444	0.542	0.038	2.542
BSSS_2	- -	**10.916**	1.392	0.653	0.013	2.107
ESM_1	0.702	- -	1.932	1.149	0.937	0.008
ESM_2	0.283	- -	0.512	0.100	0.007	2.198
ESM_3	0.095	- -	0.474	0.630	0.924	2.551
RTQ_1	6.376	0.012	- -	3.550	0.225	3.472
RTQ_2	**14.136**	0.014	- -	3.969	0.282	3.280
DGI_1	0.007	1.173	0.789	- -	0.012	5.912
DGI_2	0.006	0.864	0.668	- -	0.010	6.042
E_1	**15.654**	4.160	1.076	0.039	- -	6.587
E_2	6.297	3.332	0.845	0.039	- -	**6.648**
A_1	5.538	**7.828**	3.115	0.574	1.651	- -
A_2	5.707	**6.941**	3.423	0.575	1.584	- -
C_1	5.819	1.527	2.218	0.028	0.813	0.132
C_2	**7.229**	**7.457**	1.769	0.023	0.778	0.187
N_1	**9.998**	0.890	4.795	4.240	0.387	4.627
N_2	6.179	0.158	- -	- -	0.246	- -
I_1	0.921	0.023	0.012	0.734	1.614	0.056
I_2	0.765	0.022	0.011	0.797	1.367	0.055

	CONSCIEN	NEURO	INTELL
BSSS_1	4.157	3.660	**6.842**
BSSS_2	4.420	3.632	4.023
ESM_1	0.513	1.159	0.661
ESM_2	2.087	0.172	0.848
ESM_3	0.504	3.002	0.014
RTQ_1	4.222	0.158	1.864
RTQ_2	5.012	0.163	2.056
DGI_1	3.283	0.068	0.318
DGI_2	5.566	0.071	0.303
E_1	2.758	0.854	0.027
E_2	2.804	0.813	0.023
A_1	0.029	4.180	2.011
A_2	0.036	4.186	2.417
C_1	- -	4.744	3.976
C_2	- -	**24.488**	**8.787**
N_1	**14.771**	- -	0.028
N_2	- -	- -	- -
I_1	5.687	1.165	- -
I_2	5.855	1.206	- -

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 =

Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2; values in bold represent significant modification index values.

Table 4.6 shows that 14 of the currently fixed elements in the Λx, if set free, would improve the fit of the model significantly ($p > .01$). The matrix suggested that 14 out of the 152 possible ways of modifying the model (9,21%) would result in significant improvements to the model fit. This percentage is sufficiently small and further comments favourably on the fit of the model.

Table 4.7

Measurement model modification indices for theta-delta

	BSSS_1	BSSS_2	ESM_1	ESM_2	ESM_3	RTQ_1
BSSS_1	- -					
BSSS_2	- -	- -				
ESM_1	0.230	0.002	- -			
ESM_2	1.765	1.454	0.091	- -		
ESM_3	0.048	0.004	0.059	0.006	- -	
RTQ_1	4.020	0.011	0.061	0.715	0.333	- -
RTQ_2	0.678	1.151	1.249	0.519	3.729	- -
DGI_1	0.902	0.655	4.389	0.270	**7.656**	1.332
DGI_2	0.219	0.649	5.102	0.002	5.865	0.053
E_1	4.301	6.422	1.496	0.551	2.700	0.001
E_2	0.031	0.435	1.985	1.388	1.984	0.464
A_1	1.089	**6.897**	0.391	0.005	4.244	0.005
A_2	0.008	4.186	0.218	1.884	0.046	4.082
C_1	2.334	0.318	0.057	0.172	0.179	0.088
C_2	3.744	0.084	1.416	3.724	0.397	1.112
N_1	0.762	2.415	0.100	0.114	0.513	0.683
N_2	0.817	0.061	1.440	0.012	0.830	0.001
I_1	0.242	0.949	0.305	0.169	0.031	0.015
I_2	1.460	0.021	0.023	1.233	0.292	0.138

	RTQ_2	DGI_1	DGI_2	E_1	E_2	A_1
RTQ_2	- -					
DGI_1	0.629	- -				
DGI_2	0.043	- -	- -			
E_1	0.096	3.972	5.247	- -		
E_2	0.301	0.005	0.724	- -	- -	
A_1	0.086	**7.039**	4.857	0.340	0.022	- -
A_2	4.680	0.271	0.048	5.497	3.702	- -
C_1	0.032	0.236	0.118	2.558	1.890	0.805
C_2	2.497	3.642	3.074	4.115	3.332	0.315
N_1	0.062	0.111	2.791	0.713	3.215	0.399
N_2	0.064	1.792	0.302	0.414	0.975	3.508
I_1	0.049	0.075	0.007	1.014	0.133	0.014
I_2	0.271	0.003	0.138	0.083	1.264	0.436

	A_2	C_1	C_2	N_1	N_2	I_1	I_2
A_2	- -						
C_1	0.313	- -					
C_2	0.107	- -	- -				
N_1	3.341	2.769	1.935	- -			
N_2	5.963	1.041	**7.961**	- -	- -		
I_1	0.017	0.333	5.426	0.085	0.065	- -	
I_2	0.167	0.080	**8.315**	0.068	0.071	- -	- -

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2; values in bold represent significant modification index values.

The modification indices for the theta-delta matrix (table 4.7) revealed that five covariance terms out of the possible 171 (2,92%) terms in the matrix were significant (> 6.64). Hence, a mere 2.92% of the values, if set free, would significantly improve the fit of the model ($p < .01$). This small percentage of large significant modification index values that were obtained for Θ_δ once again commented favourably on the fit of the measurement model.

In conclusion, the small percentage of large standardised residuals and the small percentage of large modification index values obtained for Λx and Θ_δ commented favourably on the fit of the measurement model.

4.5.4 Decision on the fit of the measurement model

Based on the spectrum of goodness-of-fit statistics, the distribution of standardised residuals and the small percentage of large modification indexes calculated for Λx and $\Theta\delta$, good model fit was concluded. The measurement model parameter estimates were therefore considered plausible in reproducing the observed covariance matrix and an interpretation of the measurement model parameter estimates and squared multiple correlations (R^2) for the indicators was warranted.

4.5.5 Measurement model parameter estimates and squared multiple correlations

The evaluation of the magnitude and statistical significance of the slope of the regression of the observed variable loadings onto their particular latent variables provided information with regards to the validity of the various measures contained in the measurement model. In order for any measure to provide a valid reflection of the specific latent variable it was design for, it is crucial that the slope of the regression of X_i on ξ_j in the model should be significant (Diamantopouls & Siguaw, 2000). Table 4.8 reflects the unstandardised lambda-X matrix of the *Client Risk-Tolerance* measurement model. More specifically, table 4.8 displays the regression coefficients of the regression of the manifest variables on the latent variables they are connected to. Significant indicator loadings (regression coefficients) would be interpreted to mean that the indicators successfully, i.e. validly, reflect the latent variables they were intended to measure. The loadings of the manifest variables on the latent variables are considered significant ($p < .05$) if the t-values (reflected by the third value) exceeded the absolute value of |1.6449|.

Table 4.8

Measurement model unstandardised lambda-X matrix

	SS	ESM	RT	DG	EXTRA	AGREE
BSSS_1	0.532 (0.065) **8.182**					
BSSS_2	0.759 (0.057) **13.294**					
ESM_1	- -	0.345 0.034) **10.171**				
ESM_2	- -	0.424 (0.040) **10.506**				
ESM_3	- -	0.390 (0.041) **9.405**				
RT_1	- -	- -	0.318 (0.035) **9.072**			
RT_2	- -	- -	0.288 (0.039) **7.470**			
DG_1	- -	- -	- -	0.437 (0.054) **8.086**		
DG_2	- -	- -	- -	0.570 (0.062) **9.144**		
E_1	- -	- -	- -	- -	0.676 (0.071) **9.574**	
E_2	- -	- -	- -	- -	0.691 (0.075) **9.254**	
A_1	- -	- -	- -	- -	- -	0.502 (0.076) **6.608**
A_2	- -	- -	- -	- -	- -	0.553 (0.077) **7.219**
C_1	- -	- -	- -	- -	- -	- -
C_2	- -	- -	- -	- -	- -	- -
N_1	- -	- -	- -	- -	- -	- -
N_2	- -	- -	- -	- -	- -	- -
I_1	- -	- -	- -	- -	- -	- -
I_2	- -	- -	- -	- -	- -	- -

	CONSCIEN	NEURO	INTELL
BSSS_1	- -	- -	- -
BSSS_2	- -	- -	- -
ESM_1	- -	- -	- -
ESM_2	- -	- -	- -
ESM_3	- -	- -	- -
RT_1	- -	- -	- -
RT_2	- -	- -	- -
DG_1	- -	- -	- -
DG_2	- -	- -	- -
E_1	- -	- -	- -
E_2	- -	- -	- -
A_1	- -	- -	- -
A_2	- -	- -	- -
C_1	0.397 (0.062) **6.406**	- -	- -
C_2	0.692 (0.096) **7.228**	- -	- -
N_1	- -	0.244 (0.092) **2.655**	- -
N_2	- -	0.724 (0.155) **4.678**	- -
I_1	- -	- -	0.594 0.054) **11.015**
I_2	- -	- -	0.649 (0.058) **11.183**

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2; values in bold represent significant regression coefficient values.

Table 4.9

Measurement model completely standardised lambda-X matrix

	SS	ESM	RT	DG	EXTRA	AGREE
BSSS_1	0.617	- -				
BSSS_2	**0.956**	- -				
ESM_1	- -	**0.709**				
ESM_2	- -	**0.736**				
ESM_3	- -	0.654				
RT_1	- -	- -	**0.831**			
RT_2	- -	- -	0.671			
DG_1	- -	- -	- -	0.699		
DG_2	- -	- -	- -	**0.950**		
E_1	- -	- -	- -	- -	**0.772**	
E_2	- -	- -	- -	- -	**0.732**	
A_1	- -	- -	- -	- -	- -	0.659
A_2	- -	- -	- -	- -	- -	0.674
C_1	- -	- -	- -	- -	- -	- -
C_2	- -	- -	- -	- -	- -	- -
N_1	- -	- -	- -	- -	- -	- -
N_2	- -	- -	- -	- -	- -	- -
I_1	- -	- -	- -	- -	- -	- -
I_2	- -	- -	- -	- -	- -	--

	CONSCIEN	NEURO	INTELL
BSSS_1	- -	- -	- -
BSSS_2	- -	- -	- -
ESM_1	- -	- -	- -
ESM_2	- -	- -	- -
ESM_3	- -	- -	- -
RT_1	- -	- -	- -
RT_2	- -	- -	- -
DG_1	- -	- -	- -
DG_2	- -	- -	- -
E_1	- -	- -	- -
E_2	- -	- -	- -
A_1	- -	- -	- -
A_2	- -	- -	- -
C_1	0.507	- -	- -
C_2	**0.774**	- -	- -
N_1	- -	0.288	- -
N_2	- -	**0.801**	- -
I_1	- -	- -	**0.782**
I_2	- -	- -	**0.789**

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2; values in bold represent significant factor loading estimates (> .71).

From table 4.8 it is evident that all the indicator variables loaded significantly onto the latent variables that they were designed to reflect. This demonstrates that the various indicator variables provide to some degree a valid reflection of the latent variable they were intended to measure. According to Diamantopoulos and Siguaw (2000), one cannot solely rely on unstandardised loadings and associated t-values to derive inferences regarding the validity of the indicators, as it may be difficult to compare the validity of different indicators measuring a particular construct. Consequently, the completely standardised factor loading matrix should also be considered due to the comparative value of the standardised estimates.

The completely standardised factor loadings reflect the average change, expressed in standard deviation units, in the indicator variables associated with one standard deviation change in the latent variables to which they have been linked, given that the effect of all other variables are held constant (Diamantopoulos & Siguaw, 2000). The factor loading estimates were considered to be satisfactory if the completely standardised factor loading estimates exceeded a cut-off of .71 (Hair et al., 2006).

Table 4.9 reveals that eleven of the parcels obtained loadings greater than .71. Eight of the parcels obtained loadings that fell below the quite stringent .71 cut-off value (BSSS_1, ESM_3, RTQ_2, DGI_1, A_1, A_2, C_1, N_1). Based on these results, the identified item parcels could be regarded as problematic to a certain extent. However, except for the factor loading of N_1 (.288)[37], the factor loadings of the other item parcels on their designated latent variables were not excessively low to warrant serious concern (all loadings exceeded .500, ranging from .507 to .699).

The squared multiple correlations (R^2) for the item parcels on their designated latent variable, depicted in table 4.10, were interpreted in addition to the completely standardised lambda-X matrix. The R^2 values represent the proportion of variance in the item parcel/composite that is explained by its underlying latent variable (Prinsloo, 2011). High R^2 values are preferred, as this would indicate high indicator reliability.

Table 4.10

[37] Given the concerning results of the item analysis and the CFA conducted on the Neuroticism subscale in chapter 3, the low factor loading was not surprising. The item parcel could not be deleted from subsequent analysis due to the limited number of items for this subscale (m = 4) and the fact that at least 2 item parcels per latent variable is required.

Squared multiple correlations for X-variables

BSSS_1	BSSS_2	ESM_1	ESM_2	ESM_3	RTQ_1
0.381	0.914	0.503	0.542	0.428	0.690
RTQ_2	DGI_1	DGI_2	E_1	E_2	A_1
0.450	0.489	0.902	0.595	0.536	0.435
A_2	C_1	C_2	N_1	N_2	I_1
0.454	0.257	0.600	0.083	0.642	0.611
I_2					
0.623					

Note: BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2.

The critical factor loading of .71, suggested by Hair et al. (2006), implies a critical R^2 value of .50. High R^2 values (> .50) would indicate high indicator reliability. This indicates that a satisfactory proportion of variance in each indicator variable is explained by its underlying latent variable. Eight of the parcels obtained reliabilities that fell below the .50 cut-off value (BSSS_1, ESM_3, RTQ_2, DGI_1, A_1, A_2, C_1, N_1 indicated in table 4.10). Item parcels C_1 and N_1 raised serious concern, due to the extremely low R^2 values of .257 and .083 respectively. The values can be interpreted to mean that only approximately 25% and 8% of the variance in C_1 and N_1 is explained by the latent traits they were designed to reflect. It should also be noted that BSSS_2 and DGI_2 returned high R^2 values, .914 and .902. This implies that approximately 91% of the variance in BSSS_2 is explained by *Sensation Seeking* and 90% of the variance in DGI_2 is explained by *Delay* of *Gratification*. Both the extremely low and high R^2 values, to a certain extent, erode confidence in the measurement model and the success with which the latent variables have been operationalised.

Table 4.11 displays the completely standardised measurement error variances. These values can be interpreted as the proportion of item parcel variance that is due to systematic non-relevant variance and random error variance or the percentage of variance in the indicator variable that cannot be explained in terms of the latent variable. Values below .50 are considered ideal; indicating that less than 50% of the item parcel variance can be attributed to measurement error variance. Again, the same eight problematic indicators were identified. The results suggested that the reliability and validity of these eight indicators have been compromised. However, N_1 was the only serious concern as an extremely large proportion of the item parcel variance (91.7%) in N_1 can be ascribed to systematic non-relevant variance and random error variance. C_1 (74.3%) also raised some concern. After careful consideration, however, both item parcels were retained as there were already only two item parcels, with two items each, reflecting these respective latent variables (i.e. *Neuroticism* and *Conscientiousness*).

Table 4.11

Measurement model completely standardised solution theta-delta

BSSS_1	BSSS_2	ESM_1	ESM_2	ESM_3	RTQ_1
0.619	0.086	0.497	0.458	0.572	0.310
RTQ_2	**DGI_1**	**DGI_2**	**E_1**	**E_2**	**A_1**
0.550	0.511	0.098	0.405	0.464	0.565
A_2	**C_1**	**C_2**	**N_1**	**N_2**	**I_1**
0.546	0.743	0.400	0.917	0.358	0.389
I_2					
0.377					

Note: BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2.

The unstandardised theta-delta matrix is depicted in table 4.12. All measurement error variance estimates were statistically significant ($p < .05$) with the exception of the measurement error estimates associated with the indicators DGI_2 and N_2, which were found to be insignificant ($p > .05$). The insignificant error variance associated with DGI_2 may again be a manifestation of the problem referred to earlier, in that the *Delay of Gratification* latent variable explains a large proportion of variance in this indicator (DGI_2).

Table 4.12

Measurement model ustandardised solution theta-delta

BSSS_1	BSSS_2	ESM_1	ESM_2	ESM_3	RTQ_1
0.461	0.054	0.118	0.152	0.203	0.046
(0.061)	(0.068)	(0.016)	0.027)	0.026)	(0.020)
7.548	0.799	7.588	5.639	7.920	2.257

RTQ_2	DGI_1	DGI_2	E_1	E_2	A_1
0.102	0.200	0.035	0.310	0.414	0.328
(0.018)	(0.036)	(0.050)	(0.069)	(0.086)	(0.078)
5.514	5.516	**0.699**	4.496	4.808	4.193

A_2	C_1	C_2	N_1	N_2	I_1
0.367	0.457	0.320	0.655	0.292	0.224
(0.074)	(0.062)	(0.115)	(0.064)	(0.219)	(0.048)
4.983	7.357	2.780	10.264	**1.333**	4.700

I_2
0.255
(0.062)
4.082

Note: BSSS_1 = Brief Sensation Seeking Scale Parcel 1; BSSS_2 = Brief Sensation Seeking Scale Parcel 2; ESM_1 = Emotional Self-Management subscale Parcel 1; ESM_2 = Emotional Self-Management subscale Parcel 2; EMS_3 = Emotional Self-Management subscale Parcel 3; RTQ_1 = Risk Tolerance Questionnaire Parcel 1; RTQ_2 = Risk Tolerance Questionnaire Parcel 2; DGI_1 = Delaying Gratification Inventory Parcel 1; DGI_2 = Delaying Gratification Inventory Parcel 2; E_1 = Extraversion Parcel 1; E_2 = Extraversion Parcel 2; A_1 = Agreeableness Parcel 1; A_2 = Agreeableness Parcel 2; C_1 = Conscientiousness Parcel 1; C_2 = Conscientiousness Parcel 2; N_1 = Neuroticism Parcel 1; N_2 = Neuroticism Parcel 2; I_1 = Intellect/ Imagination Parcel 1; I_2 – Intellect/ Imagination Parcel 2; values in bold represent insignificant measurement error variances.

4.5.6 Discriminant validity

The Φ matrices depicted in tables 4.13 and 4.14 were interpreted. The Φ matrix contains the inter-correlations between the latent variables in the measurement model. Sufficiently low inter-correlations (< .90) were needed to conclude discriminant validity.

Technically, discriminant validity would be achieved if a measure of items does not correlate excessively with measures from which it is supposed to differ. When a measure fails to achieve discriminant validity, “constructs [have] an influence on the variation of more than just the observed variables to which they are theoretically related" (Henseler, Ringle, & Sarstedt, 2015, p. 116).

In table 4.13, the top value represents the unstandardised φ_{ij} estimate, the second value reflects the standard error of φ_{ij}, and the third value shows the test statistic z. Correlations exceeding a value of .90 are considered excessively high. From the results it was clear that the majority of the correlations in the phi matrix were sufficiently low, and discriminant validity between the respective constructs were attained.

Table 4.13

Measurement model unstandardised solution phi

	SS	ESM	RT	DG	EXTRA	AGREE
SS	1.000					
ESM	0.111 (0.086) **1.282**	1.000				
RTQ	0.383 (0.078) 4.942	0.170 (0.093) 1.840	1.000			
DGI	-0.140 (0.076) -1.838	0.334 (0.072) 4.669	0.089 (0.082) **1.086**	1.000		
EXTRA	0.507 (0.071) 7.102	0.342 (0.090) 3.795	0.268 (0.088) 3.046	0.066 (0.076) **0.862**	1.000	
AGREE	-0.088 (0.093) **-0.953**	0.411 (0.103) 3.990	-0.170 0.117) **-1.453**	-0.015 0.096) **-0.160**	0.280 (0.102) 2.747	1.000
CONSCIEN	-0.261 (0.093) -2.798	0.414 (0.111) 3.737	0.060 (0.097) **0.622**	0.332 (0.087) 3.819	0.158 (0.106) **1.489**	0.167 (0.114) **1.466**
NEURO	0.080 (0.094) **0.856**	-0.476 (0.130) -3.664	-0.117 (0.115) **-1.017**	-0.263 (0.117) -2.252	0.095 (0.108) **0.878**	-0.096 (0.122) **-0.785**
INTELL	0.340 (0.077) 4.403	0.366 (0.083) 4.423	0.052 (0.092) **0.565**	-0.166 (0.083) -2.010	0.328 (0.109) 3.016	0.316 (0.108) 2.931

	CONSCIEN	NEURO	INTELL
CONSCIEN	1.000		
NEURO	-0.364	1.000	
	(0.139)		
	-2.607		
INTELL	0.175	0.287	1.000
	(0.108)	(0.109)	
	1.615	-2.648	

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); values in bold represent non-significant inter-correlations.

Table 4.14

Measurement model completely standardised solution phi

	SS	ESM	RT	DG	EXTRA	AGREE
SS	1.000					
ESM	0.111	1.000				
RTQ	0.383	0.170	1.000			
DGI	-0.140	0.334	0.089	1.000		
EXTRA	0.507	0.342	0.268	0.066	1.000	
AGREE	-0.088	0.411	-0.170	-0.015	0.280	1.000
CONSCIEN	-0.261	0.414	0.060	0.332	0.158	0.167
NEURO	0.080	-0.476	-0.117	-0.263	0.095	-0.096
INTELL	0.340	0.366	0.052	-0.166	0.328	0.316

	CONSCIEN	NEURO	INTELL
CONSCIEN	1.000		
NEURO	-0.364	1.000	
INTELL	0.175	- 0.287	1.000

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; RT = Risk-Tolerance; DG = Delay of Gratification; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience).

4.5.7 Summary of the Client Risk-Tolerance measurement model

The primary purpose of fitting the measurement model was to evaluate the way in which the model represented the relationships between the *Client Risk-Tolerance* latent variables and its corresponding item parcel indicator variables. A CFA analysis was conducted via LISREL to derive the inferences made regarding the measurement model fit.

From the results of the statistical fit indices, the measurement model displayed satisfactory fit. After the hypothesis of exact fit was rejected, the null hypothesis for close fit was tested and not rejected; thus, reflecting favourably on the model fit. An inspection of the distribution of standardised residuals and percentage of large modification indices calculated for Λ_x and $\Theta\delta$ corroborated the inference of good model fit.

All the indicator variables loaded statistically significantly ($p < .05$) onto the latent variables that they were designed to reflect. This seemed to validate the claim that the various indicator variables provided a valid reflection of the latent variable they were intended to measure. However, upon closer inspection of the model parameter estimates and squared multiple correlations, it became apparent that not all indicator variables loaded highly ($\lambda_{ij} \geq .71$) onto the latent variables they were designed to reproduce, and not all indicator variable variance were sufficiently explained ($R^2 >$ .50) by its underlying latent variables. This painted a slightly less positive picture of the overall reliability and validity of the measures used to reproduce the constructs of interest. From the various matrices produced via LISREL, two item parcels raised serious concern. Item parcels C_1 (*Conscientiousness*) and N_1 (*Neuroticism*) obtained low factor loadings and excessively low R^2 values. Relatively large measurement error variances were also observed for these two indicator variables. Two other indicator variables, BSSS_2 (*Sensation Seeking*) and DGI_2 (*Delay of Gratification)* obtained unusually large R^2 values. These findings, to a certain extent, eroded confidence in the measurement model and the success with which these latent variables of interest were operationalised. In general, however, despite these concerns, reasonable lambda-X parameter estimates, measurement error terms and latent variable variances were observed.

In chapter 3 various concerns and shortcomings with regards to the reliability and validity of the measurement component were acknowledged. The analysis of scores with poor reliability and validity could jeopardise the subsequent results obtained through SEM. Therefore, the potential detrimental effects in subsequent analyses and accuracy of interpretation were noted.

However, based on the basket of evidence presented in this section it was concluded that sufficient merit for the measurement model existed and that the operationalisation of the measurement model was not completely unsuccessful. It would still be possible to derive an unequivocal verdict on the fit of the structural model, given that the proposed challenges, as pointed out, are noted and interpreted appropriately.

4.6 Structural Model

The structural model graphically depicts the potential causal relationships between the various exogenous and endogenous latent variables in the study. In order to test the causal relations hypothesised in the structural model, SEM was used to impose relations between all of the variables (both latent and manifest) accounted for in the model.

In an attempt to answer the research initiating question, comprehensive theorising in the form of a literature study culminated into a number of research hypotheses. The present study intended to empirically test the predictions made by these research hypotheses (schematically depicted in the explanatory structural model in figure 2.3). Thus, the purpose was to determine whether these hypotheses were supported by the data obtained from the sample.

4.6.1 Fitting the structural model

The *Client Risk-Tolerance* reduced structural model was fitted by analysing the covariance matrix. RML was used as the null hypothesis for multivariate normality in the observed data was rejected (table 4.3). LISREL 8.8 (Du Toit & Du Toit, 2001) was used to perform the structural equation analysis.

4.6.2 Interpretation of structural model fit and parameter estimates

In the interest of brevity only the most widely reported fit indices were discussed in relation to the fit of the various measurement models presented in chapters 3 and 4. However, the structural model fit was interpreted by inspecting a broader range of indices provided by LISREL (Diamantopoulos & Siguaw, 2000) in order to create a richer perspective on the fit of the model to the sample data. The exact fit null hypothesis (H_{02a}) that the *Client Risk-Tolerance* structural model provides a perfect account of the psychological dynamics underlying *Client Risk-Tolerance* was tested via the Satorra-Bentler chi square (χ^2) statistic (as RML estimation was used). However, it is somewhat unrealistic to assume that the model provides a perfect account of the psychological dynamics that underpin *Client Risk-Tolerance*, and therefore it was highly likely that H_{02a} would be rejected. Consequently, the close fit null hypothesis (H_{02b}) was tested by inspecting the probability of observing the sample estimate of the root mean square error of approximation (RMSEA) under the close fit null hypothesis (H_{02b}).

As with the measurement model, consideration was also given to the magnitude and distribution of the standardised residuals and the magnitude of model modification indices calculated for Γ and **B.** Standardised residuals were considered large if the values exceed + 2.58 or fell below - 2.58. Positive residuals indicate underestimation and imply the need for additional explanatory paths, whereas negative residuals indicate overestimation and suggest the need to do away with explanatory paths.

The modification indices (Diamantopoulos & Siguaw, 2000) calculated by LISREL for the Γ and **B** matrices were inspected to determine whether, by the inclusion of additional structural paths, any meaningful possibilities existed to improve the fit of the comprehensive model. A modification index value equal to, or greater than 6.64 identified those currently fixed parameters that, if set free, would improve the model fit significantly ($p < .01$).

When numerous large and significant modification index values exist, it comments negatively on the fit of the model and suggests that a number of possibilities exist to improve the fit of the model. Thus, inspection of the model modification indices for the aforementioned matrices served the primary purpose of commenting on the fit of the model. However, inspection of the model modifications calculated for the Γ and **B** matrices were also used to explore possible modifications to the current structural model, only if such modifications made substantive theoretical sense (Diamantopoulos & Siguaw, 2000). The testing of empirically driven modifications of the model was, however, not included in this study. Chapter 5 discusses and elaborates on possible model modifications suggested by the current results. These possible modifications were integrated into the recommendations for future research, where it was theoretically justifiable.

If the proposed model achieved close fit, i.e. if H_{02b} failed to be rejected, or if at least reasonable structural model fit was obtained, H_{03} – H_{017} was tested. Specifically, the statistical hypotheses formulated in chapter 3 for the path-specific substantive hypotheses were tested by investigating the statistical significance and magnitude of the path coefficients as presented in the completely standardised solutions for Γ and **B**. The significance and magnitude of the path coefficients were calculated for each hypothesised influence[38] in the model.

In addition, the squared multiple correlations (R^2) associated with each endogenous latent variable were inspected. Large R^2 values were preferred.

In the final analysis the psychological explanation of *Client Risk-Tolerance* depicted in the structural model, figure 2.3, were considered satisfactory to the extent that:

- the measurement model fitted the data well;
- the comprehensive structural model fitted the data well;
- the path coefficients for the hypothesised structural relations were significant; and
- the model explained a substantial proportion of the variance in each of the endogenous latent variables.

4.6.3 Evaluating the fit of the client risk-tolerance structural model

Figure 4.4 visually represents the fitted structural model. The full spectrum of goodness-of-fit statistics provided by LISREL 8.8 for the comprehensive LISREL model is depicted in table 4.15.

[38] The term influence refers to the effect of ξ_j on η_i or the effect of η_j on η_i.

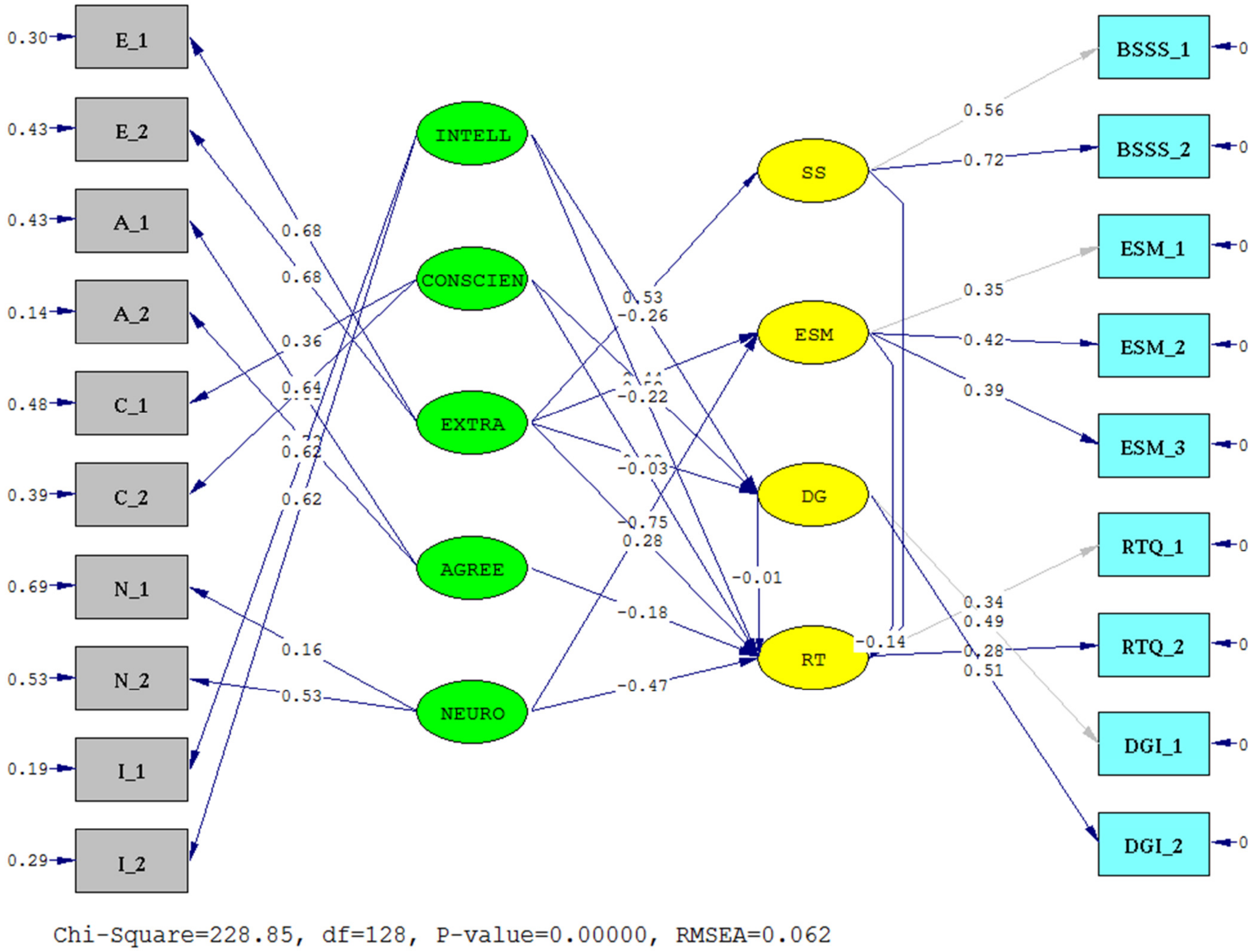


Figure 4.4. **Fitted structural model (standardised solution)**

Table 4.15

The Goodness of fit statistics for the Client Risk-Tolerance structural model

Goodness of Fit Statistics	
Degrees of Freedom	128
Minimum Fit Function Chi-Square	240.324 (P = 0.00)
Normal Theory Weighted Least Squares Chi-Square	235.552 (P = 0.00)
Satorra-Bentler Scaled Chi-Square	**228.853 (P = 0.00)**
Chi-Square Corrected for Non-Normality	646.689 (P = 0.0)
Estimated Non-centrality Parameter (NCP)	100.853
90 Percent Confidence Interval for NCP	(62.488 ; 147.065)
Minimum Fit Function Value	1.178
Population Discrepancy Function Value (F0)	0.494
90 Percent Confidence Interval for F0	(0.306 ; 0.721)
Root Mean Square Error of Approximation (RMSEA)	**0.0621**
90 Percent Confidence Interval for RMSEA	(0.0489 ; 0.0750)
P-Value for Test of Close Fit (RMSEA < 0.05)	**0.0644**
Expected Cross-Validation Index (ECVI)	1.739
90 Percent Confidence Interval for ECVI	**(1.542 ; 1.956)**
ECVI for Saturated Model	1.863
ECVI for Independence Model	**7.136**
Chi-Square for Independence Model with 210 Degrees of Freedom	1417.688
Independence AIC	**1455.688**
Model AIC	**352.853**
Saturated AIC	**380.000**
Independence CAIC	**1537.825**
Model CAIC	**620.879**
Saturated CAIC	**1201.372**
Normed Fit Index (NFI)	**0.839**
Non-Normed Fit Index (NNFI)	**0.892**
Parsimony Normed Fit Index (PNFI)	**0.628**
Comparative Fit Index (CFI)	**0.919**
Incremental Fit Index (IFI)	**0.922**
Relative Fit Index (RFI)	**0.784**
Critical N (CN)	**150.875**
Root Mean Square Residual (RMR)	0.0425
Standardised RMR	**0.0727**
Goodness of Fit Index (GFI)	**0.892**
Adjusted Goodness of Fit Index (AGFI)	**0.839**
Parsimony Goodness of Fit Index (PGFI)	0.601

Note: Values in bold represent the fit indices discussed for purposes of evaluating the overall fit of the structural model.

A Satorra-Bentler Chi-square value of 228.853 (p = 0.00) and 128 degrees of freedom was achieved. The exact fit null hypothesis (H_{02a}: RMSEA = 0) that the *Client Risk-Tolerance* structural model provides a perfect account of the psychological dynamics underlying *Client Risk-Tolerance* was rejected (p < .05).

Consequently the p-value for close fit (RMSEA < .05) was considered and the close fit null hypothesis was not rejected (.0644, p > .05). Therefore, close fit was concluded. The model achieved an RMSEA value of .0621, indicating good model fit (see proposed cut-off values in table 3.2 by Hair et al. 2006). The upper bound of the 90 percent confidence interval for RMSEA = (.0489; .0750) also fell below the target value of .08. Further to this, the SRMR (.0727) fell below the suggested .08 cut-off value (Hair et al., 2006) substantiating the conclusion of close model fit.

The expected cross-validation Index (ECVI) focuses on overall error. It is proposed as a means to assess the likelihood that the model cross-validates in similar-size samples from the same population (Byrne, 2010). The value expresses the discrepancy between the fitted covariance matrix in the current analysed sample, and the expected covariance matrix that would be obtained in another sample of equivalent size (Byrne, 2010; Diamantopoulos & Siguaw, 2000). In the application of the ECVI the model's ECVI index is computed and compared to the independence model and the saturated model. The ECVI values are then placed in rank order. In the case that the ECVI is the smallest of the achieved values, a model more closely resembling the fitted model seems to have a better chance of being replicated in a cross-validation sample than the saturated or independence models (Byrne, 2010). Table 4.15 indicates that the ECVI (1.739) was smaller than the value obtained for the independence model (7.136). The model EVCI (1.739) was also marginally smaller than the saturated model (1.863). Based on these results it is evident that a model more closely resembling the fitted model seemed to have a better chance of being replicated in a cross-validation sample than the independence models. However, it only has a slightly better chance than the saturated model.

Akaike's information criterion (AIC) and the consistent version of the AIC (CAIC) comprises what are known as information criteria and are used to compare models (Byrne, 2010). Information criteria address the issue of model parsimony in the assessment of model fit by taking the statistical goodness-of-fit, as well as the number of estimated parameters into consideration (Byrne, 2010). Similar to the ECVI, the model AIC and CAIC must be compared to those of the independence- and the saturated models, with smaller values representing a better fit of the hypothesised model (Hu & Bentler, 1995). The model AIC (352.853) suggested that the fitted measurement model provided a more parsimonious fit than the independent model (1455.688) and the saturated model (380.000). Similarly, the CAIC (620.879) achieved a value smaller than both the independence model (1537.825) and the saturated model (1201.372). These results provided further support for a good fitting model.

The comparative fit indices (CFI, NNFI) contrast how much better the given model reproduced the observed covariance matrix than a baseline model which is usually an independence or null model ('a priori'). Better model fit is indicated by values closer to unity (1.00). However, Hair et al. (2006) suggested that values above .92 provide a strong indication of a well-fitting model. Diamantopoulos and Siguaw (2000) suggested a slightly lower benchmark value .90. The results reflected in table 4.15 shows that the CFI (.919) and IFI (.922) met the suggested criteria. The NNFI (.892) marginally missed the cut-off. All in all, satisfactory comparative fit relative to the independent model was shown.

The critical N (CN) value focused on the adequacy of the sample size. The CN focuses on estimating the size that a sample must achieve in order to be sufficient to yield an adequate model fit for an X^2 test (Byrne, 2010). The generally accepted benchmark value indicating that a model is an adequate representation of the data is CN > 200. The critical N value (150.875) in this instance fell below the generally accepted rule-of-thumb (CN > 200). However, Diamantopoulos and Sigauw (2000) argued that the value of the CN statistic itself, and the suggested rule-of-thumb have been contested in the literature and should therefore be used with caution.

The goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI) are absolute fit indices. The computation of absolute fit indices does not depend on a relative comparison with a baseline model (as with relative fit indices), and instead compares the hypothesised model with no model at all (Byrne, 2010; Hu & Bentler, 1995). The GFI indicates how closely the model comes to perfectly reproducing the observed covariance matrix. The AGFI differs from the GFI in that it adjusts for the degrees of freedom in the model (Byrne, 2010). Both these index values should range between 0 and 1, with values exceeding .90 indicating acceptable model fit (Diamantopoulos & Sigauw, 2000). In this instance, the GFI (.892) and AGFI (.839) fell slightly below the benchmark value of acceptable fit (> .90). Once again, however, this was but a marginal difference.

In conclusion, the CN, GFI, and AGFI created a slightly less positive picture of the fit of the model in comparison to the other indices discussed in this section. However, in general, the selected fit indices seemed to indicate that the proposed structural model was able to reproduce the observed covariance matrix to a degree of accuracy that warranted sufficient faith in the structural model and the derived parameter estimates.

The standardised residuals and modification indices, discussed in the next sections, also serve the purpose of commenting on the quality of the model fit.

4.6.4 Comprehensive LISREL model standardised residuals

Table 4.16 presents a summary of the standardised variance-covariance residuals. Sixteen large residuals were observed (i.e. residuals greater than |2.58|). This implies that 8.42%[39] of unique observed variance-covariance terms were poorly estimated by the model. This result is satisfactory, although not ideal.

[39] The residual matrix for the model contains ([19x20]/2) = 190 elements.

Table 4.16

Summary Statistics for the Client Risk-Tolerance model standardised residuals

Description	**Values**
Smallest Standardised Residual	-84.890
Median Standardised Residual	0.000
Largest Standardised Residual	5.957
Largest Negative Standardised Residuals	
Residual for RTQ_2 and BSSS_2	-3.871
Residual for DGI_1 and RTQ_1	-3.212
Residual for E_2 and BSSS_2	-4.890
Residual for A_1 and BSSS_2	-3.233
Residual for C_1 and BSSS_1	-2.836
Residual for C_1 and BSSS_2	-4.118
Residual for C_2 and BSSS_2	-2.938
Residual for N_1 and BSSS_1	-2.669
Residual for N_1 and BSSS_2	-2.676
Residual for I_1 and DGI_2	-2.647
Largest Positive Standardised Residuals	
Residual for DGI_2 and ESM_3	2.638
Residual for E_1 and DGI_2	5.957
Residual for A_2 and E_2	3.406
Residual for N_1 and A_2	2.630
Residual for N_1 and C_1	2.921
Residual for I_2 and C_2	2.795

Note: RTQ_1 & RTQ_2 = Risk-Tolerance; BSSS_1 & BSSS_2 = Brief Sensation Seeking Scale; DGI_1 & DGI_2 = Delay of Gratification; E_1 & E_2 = Extraversion; A_1 & A_2 = Agreeableness; N_1 = Neuroticism; C_1 & C_2 = Conscientiousness; I_1 & I_2 = Openness to Experience; ESM_3 = Emotional Self-Management.

A stem-and-leaf plot allows for the collective investigation of all standardised residuals (Diamantopoulos & Siguaw, 2000). The stem-and-leaf plot of the *Client Risk-Tolerance* structural model is depicted in figure 4.5. The stem-and-leaf plot of a good fitting model would be characterised by residuals that are distributed approximately symmetrically around zero. As is evident from figure 4.5, the stem-and-leaf plot contained an excess of residuals on the negative side, which indicated that the covariance terms were symmetrically overestimated. Six of the 16 large residuals were positive.

```
- 4|91
 - 3|922
 - 2|98776655320
 - 1|98888765555444443322222111 0000
 - 0|9998888777777765555433333222222221111100000000000000000000000000000000000
   0|1112222333444444555555666666677 89999
   1|00011123344455556678899
   2|11122245666689
   3|4
   4|
   5|
   6|0
  11|7
```

***Figure 4.5*. Stem-and-leaf plot of the Client Risk-Tolerance structural model standardised residuals**

The Q-plot of the *Client Risk-Tolerance* structural model depicted in figure 4.6 was also considered. Data points that fall on the 45-degree reference line indicate perfect model fit. Data points that swivel slightly away from the 45-degree reference line indicate good model fit. The Q-plot in figure 4.6 shows that die data points were not perfectly distributed around the desired 45-degree reference line. This commented negatively on the fit of the model. However, the deviation was not large enough to raise serious concerns that the model fitted poorly and supported the findings inferred from the goodness-of-fit statistics, namely that reasonable evidence exist that close fit was obtained.

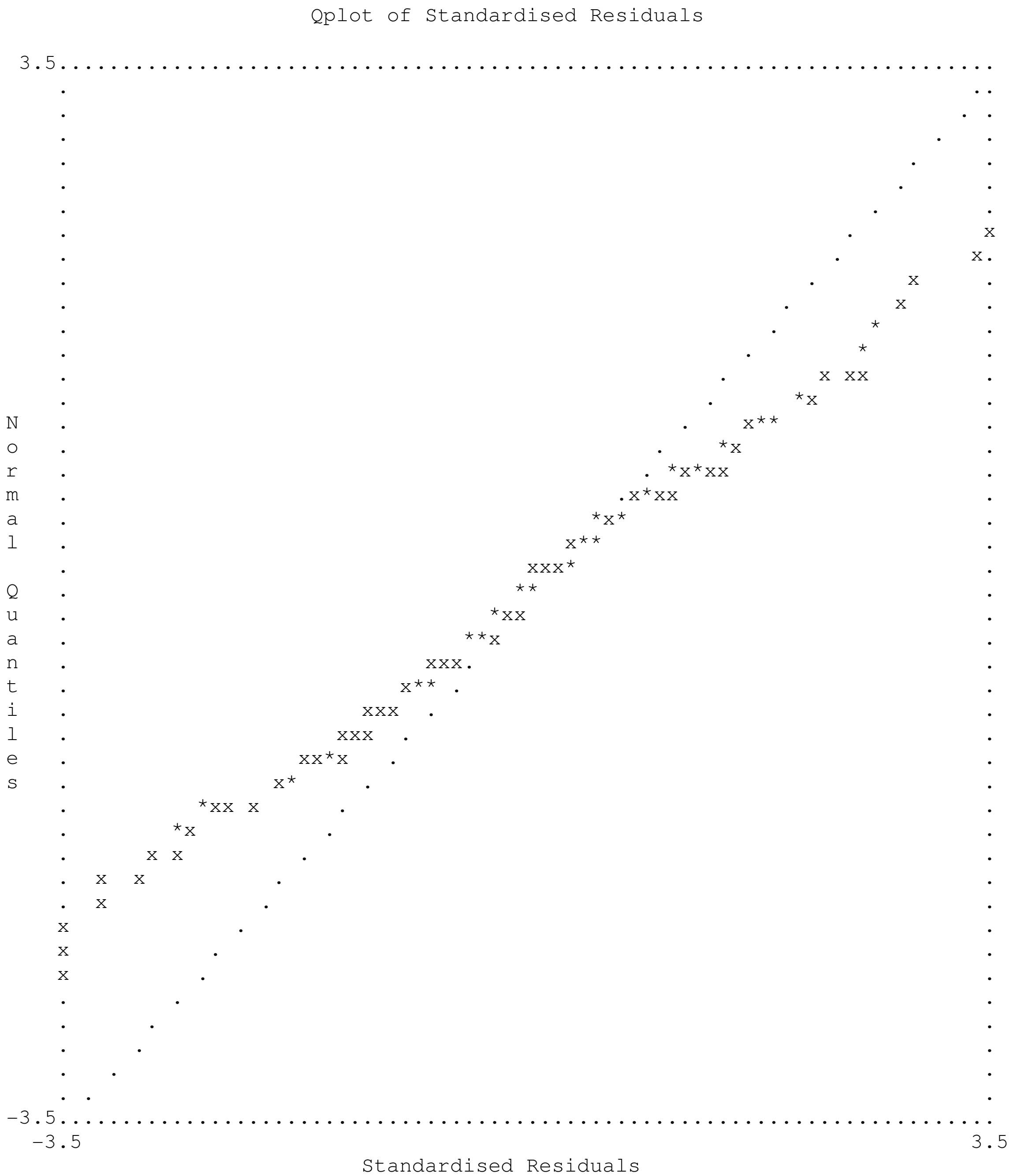


Figure 4.6. **Q-plot for the structural model standardised residuals**

4.6.5 Structural model modification indices

As with the measurement model, the structural model modification indices were inspected for the primary purpose of commenting on the model fit. In addition to this, the modification indices, calculated for gamma and beta, indicate possible ways of modifying the *Client Risk-Tolerance* structural model. This information was used to argue suggestions for future research on possible model modifications (included in chapter 5).

A value that exceeds the critical chi-square value of 6.64 indicates parameters that, if set free, would improve the fit of the model significantly ($p < .01$). The modification indices calculated for the fixed gamma parameters in the gamma matrix, presented in table 4.17, revealed that four additional paths would significantly improve the fit of the structural model. In other words, four parameters, if set free, would improve the fit of the model significantly ($p < .01$). Thus, 50% of the possible additional paths between exogenous and endogenous latent variables currently not included in the model would significantly improve the fit of the structural model. The parameter with the highest modification index-value for the gamma matrix was the addition of a path allowing *Neuroticism* to exert an influence on *Delay of Gratification*, followed by paths allowing *Conscientiousness* to exert an influence on *Sensation Seeking*, *Agreeableness* to exert an influence on *Emotional Self-Management* and *Intellect/ Imagination* (referred to as *Openness to Experience* in the model) *to* exert an influence on *Sensation Seeking.*

Table 4.17

Structural model modification indices for gamma

	INTELL	CONSCIEN	EXTRA	AGREE	NEURO
SS	**6.674**	**13.195**	- -	2.555	1.940
ESM	1.017	- -	- -	**9.580**	- -
DG	- -	- -	- -	0.244	**18.475**
RT	- -	- -	- -	- -	- -

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; DG = Delay of Gratification; RT = Risk-Tolerance; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); values in bold represent significant modification index values.

The modification indices calculated for the fixed beta parameters in the beta matrix revealed that three parameters, if set free, out of nine additional paths between endogenous latent variables (33,33%) would significantly improve the fit of the structural model. The results depicted in table 4.18 suggested the addition of a path allowing *Emotional Self-management* to exert a positive influence on *Delay of Gratification*. Moreover, it suggested the addition of paths allowing *Delay of Gratification to* exert an influence over *Sensation Seeking* and *Emotional Self-Management.*

Table 4.18

Structural model modification indices for beta

	SS	ESM	DG	RT
SS	- -	0.912	**6.922**	0.875
ESM	0.020	- -	**8.562**	0.011
DG	0.243	**12.530**	- -	0.049
RT	- -	- -	- -	- -

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; DG = Delay of Gratification; RT = Risk-Tolerance; values in bold represent significant modification index values.

4.6.6 Structural model parameter estimates and squared multiple correlations

In order to determine whether each of the hypothesised theoretical relationships (H_{03} – H_{017}) was supported by the data, empirical evidence regarding the linkages between the various endogenous (η) latent variables and between the exogenous (ξ) and endogenous (η) latent variables were examined. Diamantopoulos and Siguaw (2000) suggest an evaluation of four components when assessing the structural model relations. Firstly, the statistical significance ($p < .05$) of the parameter estimates should be inspected. Assuming that the parameter estimates are significant, the second issue to consider is the magnitude of the parameter estimates indicating the strength of the hypothesised relationships. Thirdly, the signs of the parameters representing the paths between the latent variables and the nature of the causal effects hypothesised between the latent variables should be examined. Finally, the squared multiple correlation (R^2) for each of the endogenous latent variables in the model should be considered, i.e. the amount of variance in each endogenous variable explained by the latent variable causally related to it.

The parameters of interest are the freed elements reported in the beta (**B**), gamma (Γ) and psi (**Ψ**) matrices. Each of the unstandardised matrices consists of three values of importance - unstandardised parameter estimates, standard error terms and t-values. The unstandardised parameter estimates indicates the average change in an endogenous latent variable from a unit change in an exogenous or endogenous latent variable, assuming all other exogenous and endogenous latent variables are being held constant (Diamantopoulos & Siguaw, 2000).

The unstandardised gamma matrix depicted in table 4.19 shows the unstandardised parameter estimates, standard errors and t-values for the relationships hypothesised to exist between the exogenous latent variables and the endogenous latent variables.

Table 4.19

Structural model unstandardised gamma matrix

	INTELL	CONSCIEN	EXTRA	AGREE	NEURO
SS	- -	- -	0.530	- -	- -
			(0.117)		
			4.529		
ESM	- -	- -	0.441	- -	-0.749
			(0.099)		(0.131)
			4.461		**-5.703**
DG	-0.263	0.519	0.077	- -	- -
	0.099)	(0.102)	(0.091)		
	-2.646	**5.077**	0.846		
RT	-0.220	-0.029	0.276	-0.179	-0.469
	(0.141)	(0.215)	(0.287)	(0.127)	(0.497)
	-1.556	-0.133	0.960	-1.413	-0.944

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; DG = Delay of Gratification; RT = Risk-Tolerance; EXTRA = Extraversion; AGREE = Agreeableness; CONSCIEN = Conscientiousness; NEURO = Neuroticism; INTELL = Intellect/ Imagination (Openness to Experience); values in bold represent significant regression coefficients.

The unstandardised gamma matrix was interpreted to assess the significance of the estimated path coefficients γij, expressing the strength of the influence of Ksi (ξ_j) on Eta (η_i). The unstandardised γij estimates are statistically significant ($p < .05$) if the corresponding t-value is greater than |1.6449| (Diamantopoulos & Siguaw, 2000)[40]. Additional insights on the strength of the structural relationships were gained from the completely standardised parameter estimates provided by LISREL (Diamantopoulos & Sigauw, 2000). The major advantage of the completely standardised solution is that it allows for comparison across structural equations, because the parameter estimates for gamma are unaffected by variance in the unit of measurement of the latent variables (Diamantopoulos & Siguaw, 2000). The completely standardised gamma parameter estimates are presented in table 4.20.

[40] Since the alternative hypotheses are typically formulated as directional alternative hypotheses the test of the significance of the unstandardised parameter estimates should be treated as a directional test. Assuming a 5% significance level the critical z-score should therefore be |1.6449| rather than |1.96|. A critical z-value of 1.96 would have been appropriate if the alternative hypothesis would be formulated as a non-directional hypothesis.

Table 4.20

Structural model completely standardised solution gamma

	INTELL	CONSCIEN	EXTRA	AGREE	NEURO
SS	- -	- -	**0.530**	- -	- -
ESM	- -	- -	**0.441**	- -	**-0.749**
DG	-0.263	**0.519**	0.077	- -	- -
RT	-0.220	-0.029	0.276	-0.179	-0.469

Note: Values in bold represent significant regression coefficients.

From table 4.19, it is evident that only five of the 11[41] t-values exceeded the 1.6449 rule of thumb and was thus considered statistically significant. Of the five significant hypothesised relationships contained in the gamma matrix, one value, i.e. H_{012}, did not reflect the sign/direction associated with the original hypothesised effect and could therefore not be rejected. The following null hypotheses were rejected ($p < .05$): H_{06}: $\gamma_{13} = 0$; H_{013}: $\gamma_{32} = 0$; H_{016}: $\gamma_{23} = 0$; H_{017}: $\gamma_{25} = 0$. The findings were interpreted in terms of the hypotheses listed in chapter 3.

Hypothesis 5: Extraversion (ξ_3) has a positive linear effect on Sensation Seeking (η_1).

The results in tables 4.19 and 4.20 indicate that the hypothesised path of *Extraversion* on *Sensation Seeking* was supported (SEM path coefficient = .530). The sign of the parameter estimate corresponded to the theorising that underpinned the path and it could be concluded that *Extraversion* (ξ_3) has a statistically significant positive effect on *Sensation Seeking* (η_1). H_{06}: $\gamma_{13} = 0$ could be rejected in favour of H_{a6}: $\gamma_{13} > 0$[42].

Hypothesis 12: Conscientiousness (ξ_2) has a positive linear effect on Delay of Gratification (η_3)

[41] *Emotional Self-Control* was removed from the *Client Risk-Tolerance* structural model and was not included in further analyses. Hence, hypothesis 14 could not be tested formally and a reduced *Client Risk-Tolerance* structural model with 11 gammas, instead of the originally hypothesised 12, was fitted.

[42] The overarching substantive research hypothesis (Hypothesis 1) can be dissected into exact and close fit null hypotheses for the measurement model (H01a and H01b) and the structural model (H02a and H02b). Therefore, the numbers assigned to the path specific hypotheses, for e.g. Ha6, does not coincide with the actual hypotheses, in this case Hypothesis 5.

The hypothesised positive relationship between *Conscientiousness* and *Delay of Gratification* (SEM path coefficient = .519) was found to be statistically significant. Therefore, H_{013}: $\gamma_{32} = 0$ could be rejected in favour of H_{a13}: $\gamma_{32} > 0$. This outcome provided support for the relationship between ξ_2 and η_3 in the structural model.

Hypothesis 15: *Extraversion* (ξ_3) has a positive linear effect on *Emotional Self-Management* (η_2)

The results indicated that the path of *Extraversion* on *Emotional Self-Management* was supported (SEM path coefficient = .441). Moreover, the result corroborated the originally hypothesised direction and it could be concluded that *Extraversion* (ξ_3) has a significant positive effect on *Emotional Self-Management* (η_2). Therefore, H_{016}: $\gamma_{23} = 0$ could be rejected in favour of H_{a16}: $\gamma_{23} > 0$.

Hypothesis 16: *Neuroticism* (ξ_5) has a negative linear effect on *Emotional Self-Management* (η_2)

The hypothesised relationship between *Neuroticism* and *Emotional Self-Management* was statistically significant and large (SEM path coefficient = -.749). The sign of the parameter estimate corresponded with the original hypothesised direction. Therefore, H_{017}: $\gamma_{25} = 0$ could be rejected in favour of H_{a17}: $\gamma_{25} < 0$ and the relationship between ξ_5 and η_2 was confidently confirmed.

The results contained in the gamma matrix further revealed that there were six path coefficients with [t-value < |1,6449|]. However, seven hypotheses were not corroborated. One value, i.e. H_{012}, did not reflect the sign/direction associated with the original hypothesised effect and could therefore not be rejected. The seven hypotheses that were not corroborated included H_{03}, H_{04}, H_{05}, H_{07}, H_{08}, H_{011}, and H012.

Hypothesis 2: *Openness to Experience* (ξ_1) has a positive linear effect on *Risk-Tolerance* (η_4)

Hypothesis 11: *Openness to Experience* (ξ_1) has a positive linear effect on *Delay of Gratification* (η_3)

The output indicated that *Openness to Experience (Intellect/ Imagination)* did not have a statistically significant effect on *Risk-Tolerance*. Therefore, H_{03}: $\gamma_{41} = 0$ could not be rejected in favour of H_{a3}: $\gamma_{41} > 0$. Moreover, the hypothesised positive relationship between *Openness to Experience* and *Delay of Gratification* was not corroborated. The sign of the parameter estimate was in a negative direction and therefore did not correspond with the original hypothesised positive direction. Thus, H_{012}: $\gamma_{31} = 0$ could not be rejected in favour of H_{012}: $\gamma_{31} > 0$.

Hypothesis 3: *Conscientiousness* (ξ_2) has a negative linear effect on *Risk-Tolerance* (η_4)

The evidence suggested that the hypothesised negative relationship between *Conscientiousness* and *Risk-Tolerance* was not statistically significant. Therefore, H_{04}: $\gamma_{42} = 0$ could not be rejected in favour of H_{a4}: $\gamma_{42} < 0$.

Hypothesis 4: *Extraversion* (ξ_3) has a positive linear effect on *Risk-Tolerance* (η_4)
Hypothesis 10: *Extraversion* (ξ_3) has a positive linear effect on *Delay of Gratification* (η_3)

The hypothesised positive relationship between *Extraversion* and *Risk-Tolerance* was not corroborated. Further to this, the effect of *Extraversion* on *Delay* of *Gratification* was not statistically significant. Therefore, H_{05}: $\gamma_{43} = 0$ could not be rejected in favour of H_{a5}: $\gamma_{43} > 0$, and H_{011}: $\gamma_{33} = 0$ could not be rejected in favour of H_{011}: $\gamma_{33} > 0$.

Hypothesis 6: *Agreeableness* (ξ_4) has a positive linear effect on *Risk-Tolerance* (η_4)

The results indicated that *Agreeableness* did not have a statistically significant effect on *Risk-Tolerance*. Therefore, H_{07}: $\gamma_{44} = 0$ could not be rejected in favour of H_{a7}: $\gamma_{44} > 0$.

Hypothesis 7: *Neuroticism* (ξ_5) has a negative linear effect on *Risk-Tolerance* (η_4)

The effect of *Neuroticism* on *Risk-tolerance* was not statistically significant. Therefore, H_{08}: $\gamma_{45} = 0$ could not be rejected in favour of H_{a8}: $\gamma_{45} < 0$.

The unstandardised beta matrix in table 4.21 was used to assess the significance of the estimated path coefficients β_{ij}, expressing the strength of the influence of η_j on η_i. The unstandardised β_{ij} estimates are statistically significant ($p < .05$) if the corresponding z-value is greater than |1.6449| (Diamantopoulos & Siguaw, 2000). The completely standardised beta parameter estimates reflect the average change, expressed in standard deviation units, in the endogenous latent variables, directly resulting from a one standard deviation change in an endogenous latent variable to which it has been linked, holding the effect of all other variables constant (Diamantopoulos & Siguaw, 2000). The completely standardised beta parameter estimates are presented in tables 4.22 and was used to comment on the strength and direction of the hypothesised relationships.

Table 4.21

Structural model unstandardised beta matrix

	SS	ESM	DG	RT
SS	- -	- -	- -	- -
ESM	- -	- -	- -	- -
DG	- -	- -	- -	- -
RT	0.414	-0.143	-0.013	- -
	(0.097)	(0.343)	(0.097)	
	4.286	-0.416	-0.138	

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; DG = Delay of Gratification; RT = Risk-Tolerance; values in bold represent significant regression coefficients.

Table 4.22

Structural model completely standardised solution beta

	SS	ESM	DG	RT
SS	- -	- -	- -	- -
ESM	- -	- -	- -	- -
DG	- -	- -	- -	- -
RT	**0.414**	-0.143	-0.013	- -

Note: Values in bold represent significant regression coefficients.

According to table 4.21 only one of the freed **B** parameter estimates in the *Client Risk-Tolerance* structural model obtained a t-value greater than |1.6449| and thus, the following null hypothesis was rejected: H_{09}: $\beta_{41} = 0$.

Hypothesis 8: *Sensation Seeking* (η_1) has a positive linear effect on *Risk-Tolerance* (η_4)

Tables 4.21 and 4.22 indicated that *Sensation Seeking* (η_1) had a statistically significant positive effect on *Risk-Tolerance* (η_4) (SEM path coefficient = .414). The positive direction that was theoretically hypothesised for the relationship, was corroborated. The following null hypotheses H_{09}: $\beta_{41} = 0$ could therefore be rejected in favour of the path-specific substantive research hypotheses H_{a9}: $\beta_{41} > 0$.

The other two theorised relationships were not statistically significant [t-value < |1,6449|], and consequently the following two hypotheses could not be rejected: H_{010}: $\beta_{43} = 0$; H_{014}: β_{42}.

Hypothesis 9*: Delay of Gratification* (η_3) has a negative linear effect on *Risk-Tolerance* (η_4)

Hypothesis 13: *Emotional Self-Management* (η_2) has a positive linear effect on *Risk- Tolerance* (η_4)

The hypothesised relationships between *Delay of Gratification* and *Risk-Tolerance*, and *Emotional Self-Management* and *Risk-Tolerance* were not statistically significant. Therefore, H_{010}: $\beta_{43} = 0$ could not be rejected in favour of H_{a10}: $\beta_{43} < 0$, and H_{014}: $\beta_{32} = 0$ could not be rejected for H_{014}: $\beta_{32} > 0$.

In conclusion, the completely standardised parameter estimates revealed that of all the significant effects, the influence of *Neuroticism* on *Emotional Self-Management* was the most pronounced (-.749), followed by the effect of *Extraversion* on *Sensation Seeking* (.530), the effect of *Conscientiousness* on *Delay of Gratification* (.519), the effect of *Extraversion* on *Emotional Self-management* (.441), and the effect of *Sensation Seeking* on *Risk-Tolerance* (.414).

The psi matrices illustrate the variances in the structural error terms. More specifically, the unstandardised psi matrix depicted in table 4.23 shows the error variance estimates, standard errors and z-values for the residual terms of the structural part of the model. The completely standardised psi matrix in table 4.24 represents the magnitude of the variance coefficients in the structural error terms.

Table 4.23

Structural model unstandardised psi matrix

SS	ESM	DG	RT
0.719	0.337	0.706	0.700
(0.171)	(0.186)	(0.188)	(0.219)
4.204	1.810	**3.761**	**3.194**

Note: SS = Sensation Seeking; ESM = Emotional Self-Management; DG = Delay of Gratification; RT = Risk-Tolerance; values in bold represent significant structural error terms.

Table 4.24

Structural model completely standardised solution psi

SS	ESM	DG	RT
0.719	0.337	0.706	0.700

The results revealed that a statistically significant proportion of the variance in three of the latent variables, *Sensation Seeking*, *Delay of Gratification* and *Risk-Tolerance*, were not accounted for by the model (t-values > |1.6449|). Since the model cannot be regarded as perfect, the presence of significant psi variances was not surprising. However, the magnitude of the structural error variances was rather disappointing.

To this end it should, however, be acknowledged that this research study was the first of its kind. No attempt has been made in past research studies, to the knowledge of the researcher, to capture the complex nomological network of latent variables that affect *Client Risk-Tolerance*, in the form of a *Client Risk-Tolerance* structural model. Consequently, this research was undertaken in an attempt to set the scene for prospective research endeavours that could accumulate knowledge on the topic. Successive studies should elaborate and modify the *Client Risk-Tolerance* structural model in the hope that the magnitude of the psi variances will decrease to a satisfactory level.

The squared multiple correlations, R^2, explain the proportion of variance in each endogenous latent variable that can be accounted for by the weighted linear composite of effects linked to it in the model (Diamantopoulos & Siguaw, 2000).

Table 4.25

Squared multiple correlations for structural equations

SS	ESM	DG	RT
- - - - - - - -	- - - - - - - -	- - - - - - - -	- - - - - - - -
0.218	0.663	0.294	0.300

From table 4.25 it can be inferred that the structural model is able to explain a mere 30% of the variance in *Risk-Tolerance*. The model is therefore disappointingly unsuccessful in terms of attempts made to explain variance in the primary latent variable of interest. Furthermore, it can be observed that the model fails to substantially explain variance in *Sensation Seeking*, and *Delay of Gratification*. The R^2 values for *Emotional Self-Management* (.663) was relatively higher and thus the model explained a fair amount of variance in *Emotional Self-Management.*

It has been argued in this study that in order to gain a better understanding of the dynamics underlying *Client Risk-Tolerance*, an attempt should be made to gain a better understanding of the nomological network of latent variables that account for variance in *Client Risk-Tolerance*. The low percentages of variance in the various latent variables explained by the model demonstrate the need for elaboration of the *Client Risk-Tolerance* structural model. The need for further research is addressed in further detail in chapter 5.

Figure 4.7 indicates the parameter estimates for all the hypothesised paths in the final version of the structural model that was fitted to the data. Of the 15 original hypotheses, 14 were maintained and tested. Disappointingly only five paths yielded statistically significant results. Nine of the (maintained and tested) hypothesised effects were thus rejected.

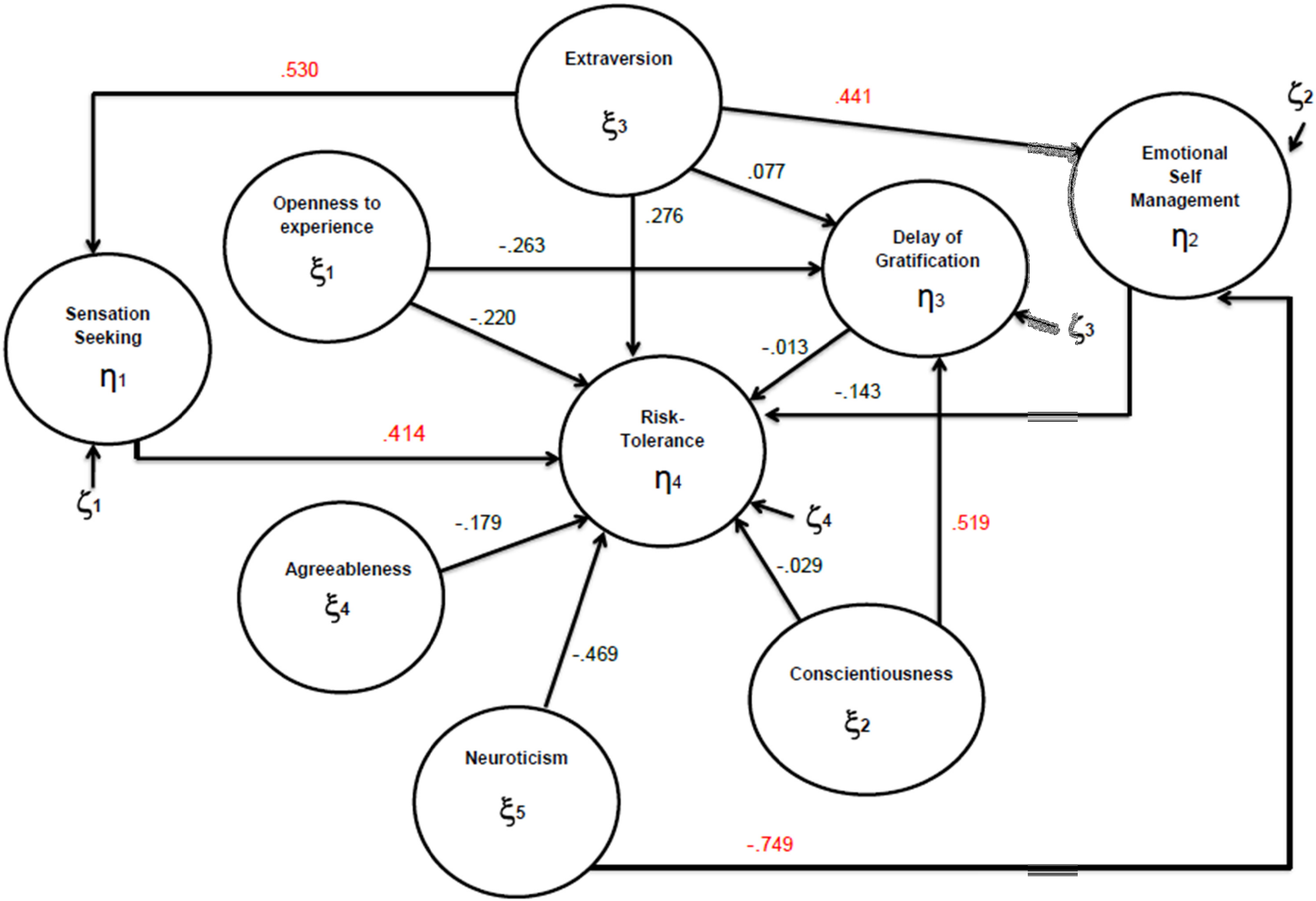


Figure 4.7. The Client Risk-Tolerance reduced structural model with hypothesised effects

4.7 Moderating Effects

A moderating or interaction effect would exist when the introduction of a moderating variable changes the magnitude or direction of the relationship between a dependent and independent variable. The slope of the regression of the dependent variable on the independent variable therefore differs in terms of sign and/or magnitude across the levels of the moderator variable.

In order to explore whether *Gender, Age, Income* and *Education* possibly act as moderators in the relationships between the various personality and emotion regulation variables, and *Risk-Tolerance*, a series of moderated multiple regressions was conducted. This specific type of regression is used to measure the hypothesised interaction effects and involves forming a multiplicative or product term, X1X2, between the independent variable hypothesised to have a main effect on the dependent variable, i.e. *Risk-Tolerance*, and the variable hypothesised to moderate this relationship, and in doing so creating a new variable. The newly created variable is entered into the regression analysis to represent the interaction effect.

More specifically, a series of standard regressions were performed separately for each demographic and socioeconomic variable. The personality and emotion regulation constructs and the interaction terms associated with each of the hypothesised moderating variables were entered into the regression equation as independent variables, and *Risk-Tolerance* was entered as dependent variable.

4.7.1 Gender as moderator

In the first moderated regression analysis, *Risk-Tolerance* was entered as dependent variable. All retained[43] personality and emotion regulation variables were entered as independent variables along with the product terms created for *Gender*. More specifically, product terms were created for the hypothesised interaction effect between *Gender* and *Conscientiousness*, *Gender* and *Agreeableness*, *Gender* and

[43] The *Emotional Self-Control* construct was removed from the *Client Risk-Tolerance* reduced structural model. Hence, this variable was not included in any further analyses conducted in this study. Therefore, *retained* in this instance refers to all other variables included in further analyses, i.e. *Extraversion*, *Agreeableness*, *Conscientiousness*, *Neuroticism*, *Intellect/Imagination (Opennes to Experience)*, *Sensation Seeking*, *Emotional Self-Management*, *Delay of Gratification* and *Risk-Tolerance*.

Neuroticism, and *Gender* and *Emotional Self-Management.* For all subsequent standard regressions the same method was followed.

The following hypotheses were investigated:

Hypothesis 17: *Gender* moderates the relationship between *Conscientiousness* and *Risk-Tolerance*

Hypothesis 18: *Gender* moderates the relationship between *Agreeableness* and *Risk-Tolerance*

Hypothesis 19: *Gender* moderates the relationship between *Neuroticism* and Risk-*Tolerance*

Hypothesis 20: *Gender* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

The results in table 4.26 indicated that the model was significant (.001, $p < .05$) and that 15.7% of the variance in *Risk-Tolerance* was explained by the various independent and moderating variables entered into the equation. *Emotional Self-Management* ($B = .459$, $p < .05$) and *Neuroticism* ($B = -.574$, $p < .05$) emerged as significant predictors of *Risk-Tolerance*. The results revealed that *Sensation Seeking* was significant at the .10 (10%) level ($B = .140$; $p < .10$). Thus, even though the 10 percent level constitutes a less stringent measure of the probability that the null hypothesis will be rejected incorrectly, assuming that it is true, it can be concluded that *Sensation Seeking* made a significant unique contribution to the equation at the 10% significance level. Moreover, evidence for *Gender* as moderating variable emerged, indicating that *Gender* significantly moderated the effect of *Emotional Self-Management* on *Risk-Tolerance* ($B = -1.469$, $p < .05$) and the effect of *Neuroticism* on *Risk-Tolerance* ($B = 1.300$, $p < .05$) in a model that contained the remaining predictors. The *Gender* x *Emotional Self-Management* interaction effect therefore statistically significantly explained unique variance in *Risk-Tolerance* not explained by the other effects in the model. Likewise the inclusion of the *Gender* x *Neuroticism* interaction effect in the regression model statistically significantly explained unique variance in *Risk-Tolerance* not explained by the other effects in the model. Consequently, hypothesis 19 and 20 were supported.

Table 4.26

Model summary: Gender as moderator

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
1	.396	.157	.104	3.47247	2.945	.001

a. Dependent Variable: ‘client risk-tolerance’
b. Predictors: (Constant), Gender_ESM, ‘neuroticism’, ‘delay of gratification’, ‘conscientiousness’, ‘extraversion’, ‘agreeableness’, ‘emotional self-management’, ‘intellect, ‘sensation seeking’, Gender_N, Gender_C, Gender_A

Table 4.27

Moderated regression analysis for Gender

		Standardised Coefficients		
		Beta	t	Sig
Model				
1.	(Constant)		3.957	.000
	‘extraversion’	.041	.597	.551
	‘agreeableness’	.081	.442	.659
	‘conscientiousness’	-.143	-.754	.452
	‘neuroticism’	-.574	-2.722	**.007**
	‘intellect	.019	.257	.797
	‘sensation seeking’	.140	1.838	.068
	‘emotional self-management’	.459	2.995	**.003**
	‘delay of gratification’	.000	-.007	.995
	Gender_C	.279	.601	.549
	Gender_A	-.232	-.481	.631
	Gender_N	1.300	3.000	**.003**
	Gender_ESM	-1.469	-2.788	**.006**

4.7.2 Age as moderator

In the second standard regression analysis the following hypotheses were tested:

Hypothesis 21: *Age* moderates the relationship between *Openness to Experience* and *Risk-Tolerance*

Hypothesis 22: *Age* moderates the relationship between *Sensation Seeking* and *Risk-Tolerance*

Hypothesis 23: *Age* moderates the relationship between *Conscientiousness* and *Risk-Tolerance*

Hypothesis 24: *Age* moderates the relationship between *Delay of Gratification* and *Risk-Tolerance*

The results of the standard regression indicated that the model was not significant (.088, $p > .05$) and that it accounted for a mere 9.3% ($R^2 = 0.093$) of the variance in *Risk-Tolerance*. In this instance, none of the variables entered into the regression made a significant unique contribution to explaining the variance in *Risk-Tolerance* scores. Hypotheses 21 to 24 were not supported by the results.

Table 4.28

Model summary: Age as moderator

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
1	.305	.093	.036	3.60171	1.622	.088

a. Dependent Variable: ‘client risk-tolerance’

b. Predictors: (Constant), Age_DG, ‘emotional self-management’, ‘conscientiousness’, ‘extraversion’, ‘agreeableness’, ‘delay of gratification’, ‘neuroticism’, ‘intellect, ‘sensation seeking’, Age_SS, Age_Open, Age_Con

Table 4.29

Moderated regression analysis for Age

Model		Standardised Coefficients		
		Beta	**t**	**Sig**
1.	(Constant)		3.555	.000
	'extraversion'	.072	.992	.323
	'agreeableness'	.017	.213	.832
	'conscientiousness'	.078	.387	.699
	'neuroticism'	-.005	-.063	.950
	'intellect	.302	1.619	.107
	'sensation seeking'	.006	.030	.976
	'emotional self-management'	.111	1.503	.134
	'delay of gratification'	-.153	-1.150	.251
	Age_Open	-.696	-1.512	.132
	Age_SS	.295	1.039	.300
	Age_Con	-.367	-.705	.482
	Age_DG	.585	1.172	.243

4.7.3 Income as moderator

In the third moderated regression analysis, *Risk-Tolerance* was entered as dependent variable. All retained personality and emotion regulation variables were entered as independent variables along with the product term created for *Income*. More specifically, a product term was created for the hypothesised interaction effect between *Income* and *Emotional Self-Management.* The following hypothesis was tested:

Hypothesis 25: *Income* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

The results from the standard regression analysis, presented in table 4.30, indicate that the model was significant (.027; $p < .05$) and that it explained 9.1% of the variance in *Risk-Tolerance*. The results revealed that *Sensation Seeking* made a significant unique contribution to the equation ($B = .200$; $p < .05$). Moreover, evidence for *Income* as moderating variable emerged, indicating that *Income* significantly moderated the effect of *Emotional Self-Management* on *Risk-Tolerance* (B = .174; p < .05) in a model that contained the remaining predictors. The *Income* x *Emotional Self-Management* interaction effect therefore statistically significantly explained unique variance in *Risk-Tolerance* not explained by the other effects in the model. Consequently, hypothesis 25 was supported.

Table 4.30

Model summary: Income as moderator

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
1	.302	.091	.049	3.57686	2.153	.027

a. Dependent Variable: ‘client risk-tolerance’

b. Predictors: (Constant), In_ESM, ‘agreeableness’, ‘extraversion’, ‘intellect, ‘sensation seeking’, ‘delay of gratification’, ‘conscientiousness’, ‘emotional self-management’, ‘neuroticism’

Table 4.31

Moderated regression analysis for Income

		Standardised Coefficients		
		Beta	t	Sig.
Model				
1.	(Constant)		4.011	.000
	‘extraversion’	.061	.858	.392
	‘agreeableness’	.041	.558	.577
	‘conscientiousness’	-.082	-1.122	.263
	‘neuroticism’	-.021	-.269	.789
	‘intellect	.025	.324	.746
	‘sensation seeking’	.200	2.695	**.008**
	‘emotional self-management’	.034	.448	.655
	‘delay of gratification’	-.013	-.175	.861
	In_ESM	.174	2.295	**.023**

4.7.4 Education as moderator

The last standard regression analysis was performed to test the following hypothesis:

Hypothesis 27: *Education* moderates the relationship between *Emotional Self-Management* and *Risk-Tolerance*

The results presented in table 4.32 revealed that the model was significant (.029, p < .05) and that 9% of the variance in *Risk-Tolerance* was explained by the various independent and moderating variables entered into the equation. The standardised coefficients presented in table 4.33 once again indicated that *Sensation Seeking* (B = .208, P < .05) made the largest unique significant contribution to explaining the variance in *Risk-Tolerance*, followed by the contribution of the interaction term Edu_ESM (*Education**Emotional Self-Management).* More specifically, evidence for *Education* as moderating variable emerged, indicating that *Education* significantly moderated the effect of *Emotional Self-Management* on *Risk-Tolerance* (B = .176, p < .05) in a model that contained the remaining predictors. The *Education* x *Emotional Self-Management* interaction effect therefore statistically significantly explained unique variance in *Risk-Tolerance* not explained by the other effects in the model. Consequently, hypothesis 27 was supported.

Table 4.32

Model summary: Education as moderator

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
1	.300	.090	.048	3.57916	2.123	.029

a. Dependent Variable: ‘client risk-tolerance’

b. Predictors: (Constant), Edu_ESM, ‘neuroticism’, ‘delay of gratification’, ‘conscientiousness’, ‘extraversion’, ‘sensation seeking’, ‘agreeableness’, ‘intellect, ‘emotional self-management’

Table 4.33

Moderated regression analysis for Education

		Standardised Coefficients		
		Beta	**t**	**Sig.**
Model				
1.	(Constant)		3.630	.000
	'extraversion'	.084	1.180	.240
	'agreeableness'	.068	.920	.359
	'conscientiousness'	-.059	-.817	.415
	'neuroticism'	.003	.039	.969
	'intellect	.043	.564	.574
	'sensation seeking'	.208	2.817	**.005**
	'emotional self-management'	.017	.218	.828
	'delay of gratification'	-.039	-.545	.586
	Edu_ESM	.176	2.239	**.026**

Figure 4.8 depicts the final conceptual *Client Risk-Tolerance* model. The significant hypothesised effects derived via SEM and the moderated multiple regression analyses are indicated.

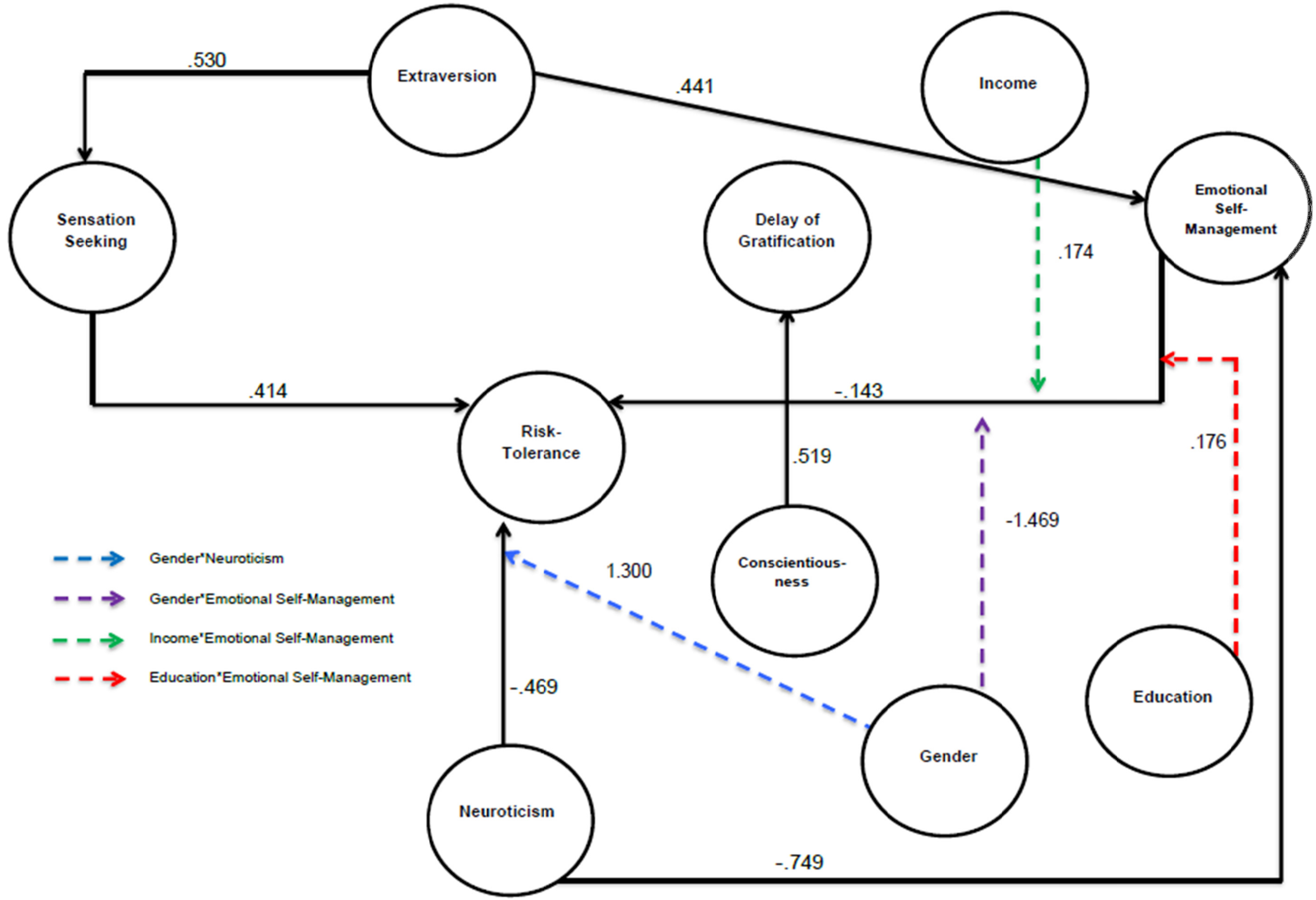


Figure 4.8. **The Client Risk-Tolerance conceptual model with significant hypothesised effects**

4.8 Summary

The purpose of this chapter was to report on the research results obtained through the data analyses in this study. More specifically this chapter served the purpose of commenting on the measurement and structural model fit, as well as reporting the results of the interaction effects of certain variables in the model. The final chapter of this dissertation will provide an in-depth discussion of the results and will focus specifically on possible structural model modifications and empirical suggestions for future research. The methodological limitations and practical implications of the research findings are also discussed.

CHAPTER 5
DISCUSSION

5.1 Introduction

In this final chapter, the research results as presented in chapters three and four are discussed in detail. A discussion of the results of the evaluation of the reduced measurement model will be included, as well as a reflection of the results of the reduced structural model and the multiple regression analyses. Further to this, this chapter aims to make recommendations for future research. More specifically, it will focus on possible model modifications that could be made in future attempts to test an elaborated/modified *Client Risk-Tolerance* structural model. This chapter will then conclude with a discussion on the limitations of the research methodology, and lastly the practical implications for financial advisors/institutions.

5.2 Results

5.2.1 Evaluation of the Client Risk-Tolerance measurement model

The overall goodness-of-fit of the reduced *Client Risk-Tolerance* measurement model (without the *Emotional Self-Control* variable[44]) was analysed in order to determine the extent to which the indicator variables successfully operationalised the latent variables comprising the reduced *Client Risk-Tolerance* structural model.

This model achieved close fit (p-value for test of close fit), supported by good incremental fit (e.g. NNFI = .937, CFI = .957) and a sufficiently small SRMR (.0347). Further to this, the small percentage of large residuals and parameters in the lambda-X and theta-delta matrices that, if set free, would improve the fit of the model, corroborated the evidence indicating good model fit.

All the indicators loaded statistically significantly ($p < .05$) on the latent variables they were designed to reflect. The results further revealed acceptable lambda-X

[44] The original proposed *Client Risk-Tolerance* measurement model (of the reduced structural model) was fitted to the data and converged, but was rendered inadmissible due to the presence of multicollinearity (as indicated by a warning message that stated that "*PHI is not positive definite*"). The inter-correlation coefficient between *Emotional Self-Management* and *Emotional Self-Control* was beyond the allowable limit of 1.00. Consequently, *Emotional Self-Control* was removed from the model and further analyses, based on the unconvincing results obtained during the investigation of its psychometric properties.

parameter estimates, except for one indicator variable (N_1), which posed serious concern. In general, low to moderate measurement error parameter estimates, and relatively high squared multiple correlation (R^2) values were observed, therefore validating the inclusion of the indicator variables as operationalisation of the latent variables in the reduced *Client Risk-Tolerance* structural model. However, N_1 once again raised serious concern, as did C_1, with extremely low R^2 values and high measurement error variance values. Therefore, for these two indicators more variance was explained by measurement error than by the latent variable in question. The discriminant validity analysis further revealed that each latent variable could be regarded as a separate qualitatively distinct, yet interrelated variable, as no inter-latent variable correlations approached unity in the parameter.

In summary, the findings pertaining to N_1 and C_1, to a certain extent eroded the confidence in the measurement model. However, it was concluded that the rest of the indicator variables provided a reasonably uncontaminated reflection of the latent variables they were tasked to reflect and that their operasionalisation was rendered relatively successful. Enough so, that an unambiguous verdict on the fit of the structural model was deemed possible. Consequently, the reduced *Client Risk-Tolerance* structural model depicted in figure 2.3 was tested via structural equation modelling (SEM).

5.2.2 Evaluation of the Client Risk-Tolerance structural model

The proposed *Client Risk-Tolerance* structural model was fitted to the data. The p-value for test of close fit indicated that the model fitted the data closely. Good model fit was supported by the RMSEA value of .0621 and the SRMR of .0727. The EVCI, AIC and CAIC further corroborated this inference. The CFI (.919), IFI (.922) and the NNFI (.892) indicated good comparative fit. The CN (150.875), GFI (.892) and AGFI (.839) created a slightly less positive picture of the fit of the model. However, it could be concluded that the selected fit indices generally pointed towards a good close fitting model. This warranted sufficient faith in the derived parameter estimates.

Consequently, the $\mathbf{B}$ and Γ matrices were investigated to determine whether the hypothesised theoretical relationships contained in the reduced structural model were supported by the data. The gamma matrix revealed that only five of the 11 path estimates were statistically significant ($p < .05$). Of the five significant hypothesised relationships contained in the gamma matrix, one value, i.e. H_{012}, did not reflect the sign/direction associated with the original hypothesised effect and could therefore not be rejected. This implied the rejection of H_{06}: $\gamma_{13} = 0$; H_{013}: $\gamma_{32} = 0$; H_{016}: $\gamma_{23} = 0$; H_{017}: $\gamma_{25} = 0$. Six path estimates were not significant which implied that H_{03}, H_{04}, H_{05}, H_{07}, H_{08}, and H_{011} could not be rejected.

The beta matrix revealed that only one of the paths estimated between the endogenous latent variables were statistically significant ($p < .05$). This implied the rejection of $\beta_{41} = 0$. The remaining two theorised relationships were not statistically significant and consequently the following hypotheses could not be rejected: H_{010}: $\beta_{43} = 0$; H_{014}: $\beta_{42} = 0$. Therefore, the results revealed empirical support for five of the 15[45] originally hypothesised paths contained in the structural model.

In the reduced *Client Risk-Tolerance* structural model, *Extraversion* was found to positively influence *Sensation Seeking*. This finding is in line with research conducted by Aluja et al. (2003). These authors reported that the excitement-seeking facet of *Extraversion*, defined as a desire for excitement and stimulation, was conceptually related to *Sensation Seeking*, i.e. the quest for varied, novel or complex sensations or experiences for the sake of such experiences as an end in itself. In as early as 1978 Eysenck and Zuckerman argued and provided empirical evidence in support of the notion that extraverts seek situations that provide them with higher levels of stimulation in order to maintain optimal levels of cortical arousal. Research has shown that extraverts are habitually in a state of lower cortical arousal, when compared to introverts (Eysenck & Eysenck, 1967). They tend to have higher sensory thresholds, and thus have smaller reactions to sensory stimulation, leading them to seek more thereof.

[45] *Emotional Self-Control* was removed from the *Client Risk-Tolerance* reduced structural model and was not included in further analyses. Hence, hypothesis 14 could not be tested formally and a reduced *Client Risk-Tolerance* structural model with 11 gammas, instead of the originally hypothesised 12, was fitted. Consequently, the number of hypotheses contained in the *Client Risk-Tolerance* reduced structural model was reduced from 15 to 14 hypotheses.

Furthermore, *Conscientiousness* was found to positively influence *Delay of Gratification*. This supports an argument put forth in a study by Chu, Ma, Li, and Han (2015), where they examined the predictors of the psychological stress response (i.e. anxiety, nervousness, depression, difficulty focussing attention and memory loss). They reported that individuals high in *Conscientiousness* have stronger levels of self-control and a higher capacity for *Delay of Gratification*. Consequently, it can be inferred that individuals who are strong willed, cautious and planful with a strong sense of self-discipline will naturally more likely display a superior ability to forego immediate gratification, in pursuit of achieving something of greater enjoyment or value, at a future point in time. In the reduced *Client Risk-Tolerance* structural model it was argued that *Delay of Gratification* mediates the relationship between *Conscientiousness* and *Risk-Tolerance*, i.e. conscientious individuals, being inclined to gather more information and make cautious decisions, may show a preference for systematic and strategic longer term investments instead of immediately rewarding, riskier investments. Investment decisions in essence are based to a large extent on the willingness to forego an immediately rewarding outcome for a lower risk accumulated outcome of modest rewards, at some future point in time. However, as will be discussed later, *Delay of Gratification* disappointingly did not have a significant effect on *Risk-Tolerance*. Consequently, there was no empirical evidence for this hypothesised mediating effect.

The results revealed that *Extraversion* exerted a positive influence on *Emotional Self-Management*, whilst *Neuroticism* exerted a negative influence on *Emotional Self-Management.* This finding was in line with the *Trait-congruency Theory*, which posits that individuals are inclined to process trait-congruent emotional information (Rusting, 1998). For example, extraverts process and recall positive stimuli faster and better, and are more likely to interpret ambiguous stimuli positively. Neurotic individuals process and recall negative stimuli faster and better, and are more likely to interpret ambiguous stimuli negatively (Ng, 2007). Moreover, the *Trait-congruency Theory* proposes that individuals are motivated to experience and maintain trait-congruent emotions, whilst trying to avoid or change trait-incongruent emotions. More specifically, this finding corroborated findings by Ng and Diener (2009) that the tendency to reduce or eliminate negative emotions or turn them into positive ones (i.e. *Emotional Self-Management*) correlated positively with *Extraversion* and negatively with *Neuroticism*. From the results it can be concluded that *Extraversion* predicts adaptive emotion regulation strategies. Individuals exhibiting this trait display the ability to preserve or savour positive emotions (i.e. *Emotional Self-Management*). In contrast to this, the results suggest that individuals higher on *Neuroticism* will more regularly use maladaptive emotional regulation strategies, such as rumination. They are more likely to make poor use of adaptive strategies to repair negative emotions, resulting in less reported *Emotional Self-Management*. Conversely, emotionally stable individuals (i.e. individuals lower on *Neuroticism*) should be more likely to change or eliminate the experience of negative affectivity (i.e. report higher *Emotional Self-Management*).

Lastly, the results derived via SEM revealed that of all the variables included in the model to exert a direct influence on *Risk-Tolerance*, only the hypothesised effect of *Sensation Seeking* on *Risk-Tolerance* was found to be significant, i.e. *Sensation Seeking* exerted a moderate positive influence on *Risk-Tolerance*. This finding corroborated the findings by Harlow and Brown (1990), and Wong and Carducci (1991) that the heightened level of arousal and stimulation desired by high sensation seekers leads to higher levels of financial *Risk-Tolerance*.

The literature review revealed that the majority of previous research studies on *Risk-Tolerance* utilised mostly correlation analysis (a method used to quantify the association between two variables) to examine isolated, i.e. direct, relationships between *objective risk-tolerance factors* and *Risk-Tolerance*. This led to inconsistent results across studies, and a consequent inconclusiveness regarding the nature of the relationships between the constructs. The lack of consensus amongst the various studies suggested that a complex and dynamic interaction between the various factors exist, i.e. *Client Risk-Tolerance* is not purely a function of direct isolated relationships with single *objective risk-tolerance* variables. It is a function of a complex interaction between various predictors that extend beyond *objective risk-tolerance variables* to include *subjective risk judgment* factors. This research was a first attempt at isolating these relationships within a nomological network of variables. The aim was to theoretically develop a conceptual model that captures, as accurately as possible, the complex set of relationships and interactions, and to test the hypothesised relationships (captured in a separate reduced structural model) and interaction effects via SEM and moderated multiple regression analyses, respectively, in an attempt to arrive at a sound conclusion regarding the factors that combine to predict *Client Risk-Tolerance*.

Given the theoretical arguments presented in chapter 2 in support of the hypothesised relationships contained in the reduced *Client Risk-Tolerance* structural model, it was rather disappointing to find that all other hypotheses were not supported by the data. That is, support was not found for the direct influence of any of the other personality variables (i.e. *Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism* and *Delay of Gratification)* on *Risk-Tolerance.* Moreover, no support for the direct effect of *Emotional Self-Management* on *Risk-Tolerance* emerged. It should also be noted that due to the removal of *Emotional Self-Control* from the measurement and structural model, the associated hypotheses could not be tested. However, the concerns in terms of the shortcomings of some the measurement instruments used in this study, should once again be acknowledged. Poor reliability and validity in measurement could jeopardise the results obtained through SEM. In light of this the results may have been negatively influenced. This is acknowledged as the greatest limitation of this research.

Nonetheless, despite the lack of evidence for the various hypothesised relationships contained in the reduced structural model, this research provided strong evidence for *Sensation Seeking* as the most important predictor of *Client Risk-Tolerance*. In chapter 2 it was argued that *Sensation seeking* is a personality factor that has consistently been found to correlate with risk-taking behaviour (Blaszczynski et al., 1986; Corter & Chen, 2006; Wong & Carducci, 1991; Young et al., 2012). *Sensation Seeking* is a biologically based personality trait and Zuckerman defines sensation seekers as individuals “who seek varied, novel or complex sensations or experiences” (Blaszczynski et al., 1986, p. 113). These individuals are prepared to take physical, social, legal and financial risks primarily for the sake of such experiences (Corter & Chen, 2006; Lauriola & Levin, 2001; Wong & Carducci, 1991), regardless of the potential risky consequences that may follow. It is not the risk per se which such an individual seeks, but the accompanying arousal gained from engaging in the risky behaviour.

The positive relationship between *Sensation Seeking* and *Risk-Tolerance* makes substantial theoretical sense. Individuals with higher levels of self-reported *Sensation Seeking*, are by definition more prepared to engage in financially risky experiences and stimulation (Corter & Chen, 2006; Lauriola & Levin, 2001; Wong & Carducci, 1991). Therefore, they will appraise financial or investment risk, i.e. risk related to loss of a portion of one's financial capital or portfolio value, as less threatening and anticipate the arousal, as a product of assuming risk, more positive than their lower *Sensation Seeking* counterparts. Lower sensation seekers are more likely to attach stronger weight to the potential negative outcome, loss or punishment associated with a financial risky activity or decision than the actual sensation or stimulation derived from engaging in that activity or decision. Further to this, it has been argued that lower sensation seekers, when compared with higher sensation seekers, perceive the time needed to recover from a negative consequence, as a result of engaging in risk, as longer (Roberti, 2004).

In addition, *Sensation Seeking* individuals are inclined to engage in activities that increase the amount of stimulation they experience (Roberti, 2004), regardless of the potential for loss or punishment. A recent study conducted by Zheng and Liu (2015) examined electrophysiological correlates associated with two different stages of risky reward processing, i.e. reward anticipation and outcome (i.e. loss or gain) appraisal. They found that sensation seekers generally experience blunted neural responses to monetary risk during both phases. Low sensation seekers exhibited increased neural responses when presented with high-risk choices versus low-risk choices during the reward anticipation phase. Moreover, low sensation seekers exhibited increased neural responses in reaction to high-risk outcomes (i.e. monetary loss or gain following a high risk choice) versus low-risk outcomes (i.e. monetary loss or gain following a low risk choice) during the outcome appraisal stage. This pattern was not observed for high sensation seekers, indicating that they exhibit a risk neutral pattern. Zheng and Liu (2015) argued that these findings are in line with the optimal arousal theory proposed by Zuckerman in 1984. This theory posits that *Sensation Seeking* behaviours are attributable to individual differences in an individual's level of optimal arousal. A departure from the optimal level may lead to the avoidance or seeking of stimulation. Firstly, it follows that high sensation seekers possess higher optimal arousal levels when compared to low sensation seekers (Zheng & Liu, 2015). Secondly, it follows that the risk perception of low versus high sensation seekers are different, where higher sensation seekers require higher stakes to perceive a difference in the riskiness attached to an investment decision. Therefore, sensation seekers typically engage in higher risk activities or decisions as a means of intensifying their neural responses. This enables them to achieve the desired or optimal level of arousal. Because of high sensation seekers' deficient or blunted brain response to monetary punishment and errors (Zheng & Liu, 2015), which, in the context of this study includes loss of financial capital as a result of a risky investment decision, they are likely to continue investing in high risk investments despite the possible punishing effects of monetary losses.

Similarly, Marotta, Cornelius, and Eadington (2002) posit that high sensation seekers are more satisfied when they experience high-level activity in the brain norepinephrine and dopamine system. Within the gambling domain, "an arousal theory of gambling suggests that the uncertainty and monetary risk related to gambling provides a higher level of stimulation and arousal which high sensation seekers desire" (Zuckerman, 1994, as cited in Marotta et al., 2002, p. 225). The arousal produced by the risky gambling activity, exclusive of the prospect of winning money, is rewarding. It could be argued that these results may be applicable to the domain of investment management.

Further to this it is argued that sensation seekers have reduced negative bias (Zheng & Liu, 2015). In the context of this study this suggests that they attribute less psychological weight to what would be perceived by low sensation seekers as an actual or anticipated detrimental loss in portfolio value. Moreover, past research has suggested that sensation seekers experience lower autonomic responses in the face of emotionally negative stimuli (Zheng & Liu, 2015). Roberti (2004) corroborated this and argued that high sensation seekers possess differing responses of the sympathetic nervous system. More specifically, high sensation seekers display lower activity of the behavioural inhibition system (BIS). The BIS is related to sensitivity to non-reward, punishment and novel experience (Farmer, 2005). In the context of this study lower BIS means that sensation seekers are less likely to experience fear, anxiety or stress when faced with making risky investment decisions that inherently include the potential for non-reward or loss. In contrast to this, lower sensation seekers possess higher BIS activity and are more likely to react with negative emotionality to the prospect of risk, or loss as a result of risk.

5.2.3 Evaluation of the multiple regression analyses results

A series of multiple regression analyses were performed in order to gain a greater understanding of the manner in which the relationships between the various personality and emotion regulation variables, and *Risk-Tolerance* were moderated by *Gender, Age, Income* and *Education*. More specifically, a series of standard regression analyses were performed separately for each of the aforementioned demographic and socioeconomic variables. The personality and emotion regulation constructs and the interaction terms associated with each of the hypothesised moderating variables were entered into the regression equation as independent variables, and *Risk-Tolerance* was entered as dependent variable.

Four of the ten[46] hypothesised moderating effects were supported by the results. That is, four hypothesised interaction effects contained in the *Client Risk-Tolerance* conceptual model explained significantly unique variance in *Risk-Tolerance*, not explained by the other main effects contained in the *Client Risk-Tolerance* conceptual model. Evidence for *Gender* as a moderating variable in the relationships between the variables of an affective nature, i.e. *Emotional Self-Management* and *Neuroticism*[47], and *Risk-Tolerance* emerged. Firstly, *Gender* emerged as a moderator in the *Emotional Self-Management – Risk-Tolerance* relationship.

In chapter 2 it was argued that if it is assumed that males and females equally engage in the use of *Emotional Self-Management* strategies (in terms of frequency) and in so doing, have the ability to effectively mitigate the anxiety provoking effects of financial decision making under conditions of risk and uncertainty, males have a superior ability to do so (McRae et al., 2008). This was based on evidence that men

[46] *Emotional Self-Control* was removed from the *Client Risk-Tolerance* model and was not included in further analyses. Hence, hypotheses 26 and 28 could not be tested formally via moderated regression analysis. Consequently, the number of hypotheses to be tested via moderated regression analysis were reduced from 12 to 10 hypotheses.

[47] It should be acknowledged that *Emotional Self-Management* and *Neuroticism* emerged as significant predictors of *Risk-Tolerance* when entered into a regression equation containing all individual difference factors (*subjective risk judgment* variables) and the hypothesised *Gender* interaction terms (*objective risk-tolerance* variables). This adds to the practical value of the tentative grid presented in Chapter 2 (figure 2.1) and is discussed in section 5.6.

apply such strategies in a manner that is quicker, more automatic and effortless (McRae et al., 2008). Moreover, whilst both gender groups frequently apply *Emotional Self-Management* strategies, females are more likely to engage in the use of maladaptive patterns of emotional regulation, such as the use of rumination, and are more likely to attach greater weight to disconfirming and subtle negative cues (Thomsen et al., 2005). Therefore, even though women use adaptive patterns of emotional regulation, the superior use of maladaptive patterns may buffer the constructive effects thereof. The evidence for the moderating effect of *Gender* in the *Emotional Self-Management – Risk-Tolerance* relationship found in this research provide some empirical grounds by which the theoretical argument presented above could be substantiated.

Moreover, the results revealed that *Gender* significantly moderated the effect of *Neuroticism* on *Risk-Tolerance*. It was argued that the attentional bias of neurotic individuals toward threatening information (Gasper & Clore, 1998), which could lead to an overestimation and avoidance of risk and thus a lower *Risk-Tolerance* level, may be strengthened by the fact that females have lower[48] thresholds for noticing negative and disconfirming information (Arcand & Nantel, 2005). In contrast to this, it was argued that being male might weaken the negative relationship between *Neuroticism* and *Risk-Tolerance*, as men are less inclined to react negatively to the slightest indication of risk. This line of reasoning was based on the *Selectivity Model* or hypothesis, as proposed by Meyers-Levy in 1989 (Arcand & Nantel, 2005) that males and females differ with regard to their information processing style. When interacting with *Neuroticism (Gender x Neuroticism)*, a trait that relates to differences in information processing styles (according to cognitive theories), *Gender* may alter the nature of the relationship between *Neuroticism* and *Risk-Tolerance* as evidenced by the results obtained in this research.

Empirical support for *Income* and *Education* as moderating variables emerged, indicating that *Income* and *Education* significantly moderated the effect of *Emotional Self-Management* on *Risk-Tolerance*, respectively. It is generally argued that higher *Income* individuals, due to a higher nominal amount to their disposal, will have a

[48] "Lower" refers to the fact that females are more likely to pay more attention to the negative details relating to an investment (such as the probability of sustaining financial loss).

natural ability to make higher risk financial decisions and will be better able to absorb financial loss. In a similar vein it is argued that higher educational attainment precedes higher levels of *Risk-Tolerance* based on superior appraisal and an overall better understanding of consequences of risky investment strategies (Hallahan et al., 2004).

However, past research attempts have failed to produce consistent results in support of these arguments. Therefore, this research argued that an individual's *Risk-Tolerance* level is primarily a manifestation of his or her emotional make-up and ability to supress or regulate affective responses evoked by decision-making under risk and uncertainty, but that one cannot ignore the individual's financial capacity to bear such risks, i.e. reflected in *Income* levels, and his/her ability to attain a rational grasp on the probabilities of risk and return, as a function of *Education*. It was argued that *Income* and *Emotional Self-Management*, and *Education* and *Emotional Self-Management* should be considered collectively in accounting for variance in *Risk-Tolerance*. The results confirmed the notion that the financial advisor's attention should be directed towards the fact that an individual's emotional willingness to assume risk and ability to bear the associated financial risk may be incompatible (Goel, 2009) – i.e. low *subjective risk judgment* coupled with high *objective risk-tolerance,* or vice versa. To this end, the results of this study support the argument that when two individuals with the same standing on *Emotional Self-Management* differ in terms of their levels of *Income*, their standing on the dependent variable *Risk-Tolerance* will vary to the extent that their *Income* levels vary. The rationale behind this relationship is based on the argument that an individual's level of *Income* may guard against, or enhance the emotional effects of real or perceived future uncertainties on an investor's *Risk-Tolerance* level. It was argued that a higher *Income* level offers the investor the ability to contribute additional financial capital should losses in portfolio value be sustained, and in doing so, provide a level of cognitive and financial security that may serve to alleviate or enhance the level of emotional comfort that he/she will experience towards a specific investment decision.

In chapter 2 it was argued that higher educational levels might serve as a catalyst for more rational risk assessment, as opposed to emotionally laden decisions, during financial decision-making. That is, higher educational attainment may enable individuals to base investment decisions on rational calculations, statistical predictions as well as past financial experience and knowledge to establish the probabilities of return. Knowing that a carefully calculated decision was made may serve to alleviate or enhance the level of emotional comfort, as a function of an individual's ability to down regulate negative emotional experiences, associated with investment decision under conditions of risk and uncertainty. The argument presented in chapter 2 that two individuals with the same standing on *Emotional Self-Management* will have different levels of *Risk-Tolerance* depending on their educational attainment, seem to hold merit based on the results attained in this study.

5.3 Data Driven Recommendations for Future Research

The hypothesised *Client Risk-Tolerance* structural/conceptual model is at best only an approximation of the true factors that underpin *Client Risk-Tolerance* in everyday financial decision-making. An important consideration that arises relates to the degree to which the model might have been misspecified, i.e. were certain irrelevant variables or paths included in the model that should not have been included, or were substantially important paths left out which could have accounted for additional variance in *Risk-Tolerance* (Mueller & Hancock, 2008). When considering possible model modifications, two important questions should be considered: 1) should insignificant paths be removed from the model, and 2) should additional paths be added to the proposed *Client Risk-Tolerance* structural model (Van Deventer, 2014).

If answers to both these questions were to be positive, remediation could only occur by respecifying the model in an attempt to derive a model more closely resembling reality. The results obtained in this study indeed suggested that the model contained various insignificant paths. It also suggested a few additional paths that could be added to the proposed model.

Van Heerden (2013) proposed that the strength/persuasiveness of the theoretical argument in support of a hypothesised path should be considered when a decision regarding its removal (based on an insignificant p-value) is made. The results from the SEM analyses revealed that five path coefficient estimates in the *Client Risk-Tolerance* structural model were statistically insignificant ($p < .05$). It is argued, however, that the removal of any one of these paths from the reduced structural model would be premature.

A first reason relates to the fact that this research study was the first of its kind. No attempt has been made in past research studies, to the knowledge of the researcher, to capture the complex nomological network of latent variables that affect *Client Risk-Tolerance*, in the form of a *Client Risk-Tolerance* structural/conceptual model. The literature study presented in chapter 2 produced a series of contrasting research results, especially with regard to the *objective risk-tolerance* factors. The lack of consensus pointed towards the underlying existence of more complex and dynamic variable interactions within a nomological network of latent variables. Instead, however, the literature review further revealed that the majority of past research studies applied methods to examine the direct relationships of the various factors with *Risk-Tolerance*, in isolation. It was argued that this constricted methodology caused the disparity and lack of consensus, which made it challenging to determine the exact nature of the relationship between each variable and *Risk-Tolerance*, respectively, as well as their respective relationships with one another.

Consequently, it failed to accurately capture the complexity of the phenomenon of interest, i.e. *Client Risk-Tolerance*. More specifically past research failed to acknowledge the role of moderators within a more complex nomological network of predictor variables. Consequently, this research was undertaken in an attempt to set the scene for prospective research endeavours that could accumulate knowledge on the topic. Thus, instead of removing paths from the first attempted *Client Risk-Tolerance* structural/conceptual model, it is recommended that successive studies retest the hypothesised paths in the hope that statistical significance would be achieved. Towards this end, attention should be focussed on improving the effectiveness with which the constructs in the initially conceptualised model were measured.

A second reason for not removing any paths from the original study, in a replication study, relates to the measurement of the personality traits that were included in this study. The lack of significant paths between any of the Big Five traits and *Risk-Tolerance* may be due to the fact that the measurement of the personality variables included in this study might have been too broad. More specifically, the use of the

Mini-IPIP as an omnibus measure of the Big Five personality traits (with only four items to measure each trait) may have contributed to a loss of explanatory power, in that possible salient lower-order factors lost significance within the broader structure. The reliance on a single broad omnibus measure of personality is likely to cause underestimated causal relationships, and hence, a lack of significant path coefficients. This is likely to lead to the exclusion of a number of potentially relevant predictor traits (Hughes, 2013).

In chapter 4 (see tables 4.17 and 4.18), the structural model modification indices were inspected and analysed for the primary purpose of commenting on the overall fit of the reduced structural model. However, the modification indices calculated for beta and gamma suggest possible ways of modifying the *Client Risk-Tolerance* structural model. The modification indices calculated for beta and gamma indicate paths that, if set free, would significantly ($p < .05$) improve the fit of the model. However, adding additional paths to the already complex model should only be considered if such proposed structural changes would make substantive theoretical sense. Should the proposed paths not be convincing, no alterations should be made to the existing structural model. Further to this, the standardised expected change for the parameters should also be evaluated. The standardised expected change indicates the estimated standardised beta and gamma coefficients that would be achieved if a currently fixed path would be freed. Freeing the path should only be considered if the resultant coefficient is of sufficient magnitude to justify doing so.

The modification indices calculated for the beta and gamma matrices suggested that seven additional paths, if set free, would improve the fit of the model significantly ($p < .05$). The parameter with the highest modification index-value (18.475) suggested the addition of a path allowing *Neuroticism* to exert a negative influence on *Delay of Gratification*. The standardised expected change for the gamma coefficient was beyond the allowable limit of 1 (-1.062). Thus, no practically significant benefit would be indicated from freeing the currently fixed gamma parameter.

The second highest modification index value (13.195) that exceeded the critical chi-square value of 6.64 suggested the addition of a path from *Conscientiousness* to

Sensation Seeking. In this instance the magnitude of the standardised expected change for the gamma coefficient (-.316) was substantial and the sign was negative. According to Zumdick (2007) a significant negative relationship between *Conscientiousness* and *Sensation Seeking* has been consistently reported across various studies. *Conscientiousness* was found to be negatively related to all underlying dimensions of *Sensation Seeking*, i.e. thrill and adventure seeking, disinhibition, boredom susceptibility and experience seeking. Zumdick (2007, p. 10) argued that individuals who score low on *Conscientiousness* could be described as "careless, imprudent, and irresponsible". In relation to the abovementioned dimensions this would firstly imply that individuals low in *Conscientiousness* are more likely to engage in risky behaviour as measured by thrill and adventure seeking. Secondly, they are more likely to seek stimulation by engaging in disinhibited activities. Thirdly, they are more likely to become bored with tasks that require an organised, careful, planned and precise approach. Thus, they would be more likely to seek novel and varied experiences in an attempt to avoid becoming bored. Lastly, individuals low in *Conscientiousness* will be more likely to seek risky experiences for the sake of doing so. It would, therefore, make substantive theoretical sense to argue that "organised, neat, orderly, practical, prompt and meticulous" (Zumdick, 2007, p. 32) individuals would be less prepared to engage in novel or complex sensations and experiences, without due consideration for the risks and consequences attached to it. In relation to *Risk-Tolerance*, one would be able to argue that such individuals (i.e. those high in *Conscientiousness*), when faced with the novelty of having to choose between different investment strategies, would engage in careful and calculated information gathering and deliberation. They would be less inclined to spontaneously adopt a risky investment strategy, due to their lower stance on *Sensation Seeking*.

The third highest modification index value (12.530) suggested that *Emotional Self-Management* should exert an influence on *Delay of Gratification*. The magnitude of the standardised expected change for the beta (.512) was satisfactory and the sign was positive. However, upon further inspection of the results (table 4.18) it became clear that the addition of a path from *Delay of Gratification* to *Emotional Self-Management* (8.562) was also suggested by the results. In this instance the magnitude of the standardised expected change (.315) was also satisfactory and in a positive direction. Thus, suggesting a bidirectional relationship. Given that both constructs fall within the broader domain of self-regulation, such a relationship would have merit. One possible argument could be that the superior ability to manage one's emotions successfully, i.e. successfully adjusting negative emotional states or engaging in activities that maintain positive emotional states (i.e. *Emotional Self-Management*) would reduce the likelihood of responding behaviourally by acting imprudently and impulsively in an attempt to provide short-term relief (i.e. *Delay of Gratification*). However, it could also be argued that such individuals (i.e. high on *Delay of Gratification*) are less likely to seek immediate gratification as a means of alleviating negative emotional states, but are rather more likely to proactively and internally alter emotional anxiety or stress (i.e. be better at *Emotional Self-Management*). Hence, one could view these variables as extensions of each other, i.e. those who are better able to delay gratification naturally possess superior abilities to self-control and thus also most probably will have the ability to regulate negative emotional responses more easily.

The fourth highest modification index value (9.580) suggested that *Agreeableness* should exert an influence on *Emotional Self-Management.* The magnitude of the standardised expected change for the gamma coefficient was sufficiently large (.665) and in a positive direction. According to Tobin, Graziano, Vanman, and Tassinary (2000, p. 656) "the best *Agreeableness* markers are emotion terms like 'kind', 'considerate', 'empathic' and 'tender-minded'". Agreeable individuals have also been described as experiencing more intense emotions, and thus have more emotions that they need to regulate or control (Tobin et al., 2000). In light of this, the possibility of a relationship between *Agreeableness* and aspects of emotion regulation is not surprising. Yet, such a relationship would probably refer to emotional regulation strategies aimed at maintaining good interpersonal relations and may not necessarily hold value within the domain of financial risk-taking. Nonetheless, Tobin et al. (2000) have argued that agreeable individuals exert more effort in their attempts to regulate the expression of emotions such as anger, sadness, or distress. However, this may only be the case when expression of such emotions poses a threat to interpersonal relationships. In exploring the biological basis related to the construct, Hass, Omura, Constable, and Canli (as cited in Robinson, Watkins, & Harmon-Jones, 2013) revealed that *Agreeableness* is related to activation of the right lateral prefrontal cortex upon exposure to negative emotional stimuli. Agreeable individuals are likely to engage more automatically in emotional regulation processes when exposed to negative stimuli. Due to stronger emotional reactions to evocative stimuli, they are likely to exert greater efforts in an attempt to regulate such emotions. Thus, it may be possible to argue that their overall superior use of emotional regulation strategies in general may transfer across domains.

The fifth highest modification index value (6.922) suggested an association between *Delay of Gratification* and *Sensation Seeking.* The standardised expected change for the beta coefficient (-.213) was satisfactory and in a negative direction. One of the few studies relating these two variables, conducted by Romer, Duckworth, Szaltman, and Park, (2010) suggested the converse, i.e. *Sensation Seeking* exerts a positive influence on *Delay of Gratification,* where sensation seekers are likely to possess superior delay abilities as frequently engaging in risky behaviour provides experiences that lead to a greater appreciation of long-term rewards. However, the modification index in this study suggests that the ability to delay gratification may lead to lower levels of *Sensation Seeking*. In other words the ability to forego immediately gratifying rewards in favour of longer term rewards leads to a decrease in the need for varied, novel sensations or experiences. Arguing such a causal linkage would seem to make substantive theoretical sense, and thus the inclusion of this path in future research is advised.

The last modification index value (6.674) suggested that *Openness to Experience* should exert an influence on *Sensation Seeking*. The standardised expected change of the gamma coefficient (.238) was in a positive direction. Given that the definitions of the two constructs overlap to a certain extent, i.e. individuals seeking varied and novel experiences, a relationship between the two constructs make theoretical sense. It could be argued that *Openness to Experience* may predispose individuals, who by definition have a desire for novel, varied and complex experiences and sensations, to seek such experiences and sensations purely for the sake of the accompanying stimulation and the satisfaction (i.e. exhibit behaviours of high *Sensation Seeking*), irrespective of accompanying risk or consequences. Thus, investors who score high on *Openness to Experience* may also be more inclined to appraise the risk related to a certain investment strategy or financial decision as less threatening and arousing and consequently, exhibit higher levels of *Client Risk-Tolerance*.

Apart from considering the modification indices for possible model modifications, the actual results were also scrutinised. The gamma matrix results revealed that *Openness to Experience* has a significant negative linear effect on *Delay of Gratification*. This result, however, did not reflect the sign/direction associated with the original hypothesised effect (i.e. positive). The hypothesis could therefore not be rejected (for the purposes of this study) and suggested a possible model modification. The theoretical relationship was initially hypothesised as positive based on the argument that individuals who are open to experience have the superior ability to divert attention inward and away from potentially tempting and frustrating aspects of the immediate environment (Mischel, Shoda, & Peake, 1988). This is based on the definition of the *Openness to Experience* trait, which encompasses the tendency to have a rich inner life and to experience the world in unusual and creative ways (McCrae & Costa, 1987). It was argued that these individuals are likely to avoid focusing on the possibility of an immediate reward by thinking about future rewards in more abstract means.

However, after careful consideration of the result obtained in this study regarding this relationship, the opposite of the original argument could also be credible and make theoretical sense. That is, individuals who are open to experience may be more likely or willing to accept immediately rewarding outcomes based on their desire for novel experience and adventure. Open individuals are described as emotionally sensitive, perhaps serving as a catalyst for seeking thrill and immediately satisfying outcomes. Successful delayers are often considered more conservative, with those more willing to accept immediately gratifying outcomes described as liberal and experimenting. Based on the characteristics inherent in the definition of *Openness to Experience* such claims would thus hold validity.

5.4 Further Recommendations

This research was a first attempt at investigating the joint effects of individual differences on *Client Risk-Tolerance* in the financial decision-making process, so as to utilise the knowledge to better inform the financial advisor of the interplay of such factors on client behaviour. Various avenues exist through which this research can be improved. For example, the inclusion of additional paths and/or different variables within the nomological network may provide a more accurate representation of the psychological process underlying *Client Risk-Tolerance*. To this end the less than ideal results in this study, point towards the need for elaboration of the *Client Risk-Tolerance* conceptual model. For example, the personality variables mentioned in the introduction to the study (*Anxiety, Optimism, Locus of Control* and *Impulsivity*) that were not explored in the literature study could be introduced to formally expand the model. It is recommended that a rigorous and systematic investigation of additional subjective (i.e. other individual differences variables) and objective factors that can be used to differentiate among *Client Risk-Tolerance*, be undertaken.

The literature review argued for the inclusion of lower-order traits within the *Client Risk-Tolerance* model in order to account for trait-specific variance, which gets lost when relying solely on the broader five factor model (Hughes, 2013). Future studies should continue to include lower-order personality traits as opposed to the broader five factor model traits. A possible measure to be considered in future research includes the NEO-PI-R (Costa & McCrae, 2008). The NEO-PI-R is measure of the Big Five factors, i.e. *Openness to Experience, Conscientiousness, Extraversion, Agreeableness* and *Neuroticism*. Additionally, the measure subsumes six subordinate or lower order facets that define each of the higher order personality factors. The NEO-PI-R thus facilitates a comprehensive assessment of personality. Future research attempts should consider including the NEO-PI-R, or selected sub-dimensions (facets) thereof, as a measure of personality. In this way trait-specific variance that could contribute increased explanatory power could be more accurately captured in the reduced structural model.

Inclusion of the role of marital status and number of dependents as moderators in the *Client Risk-Tolerance* model may be other important factors that could account for variance in *Client Risk-Tolerance*. This, however, may be difficult to operationalise as most existing studies rely on narrow operationalisations of the marital status variable. An important consideration that is overlooked in many studies is the composition of the 21st century household structure that has changed from the traditional nuclear family to include non-married couples that live together (with or without dependents), as well as single parents. Attempts should be made to reflect this complexity in the operationalisation of the marital status variable.

A final recommendation is that the current study could be expanded to empirically investigate how the *objective risk-tolerance* and *subjective risk judgment* factors of the financial advisor combine in a nomological network to influence overall financial advisor *Risk-Tolerance*, and to examine how this affects the manner in which he/she presents advice to the client. Future studies could also seek to study the effect of diverse combinations of advisor-client personalities on the advisor-client relationship. The basis for such a study rests on the assumption that the compatibility of client-advisor personalities would alter the level of openness, trust and suggestibility of the client.

5.5 Limitations

Throughout the course of this study a number of limitations were identified.

Firstly, the sample of 205 clients, although considered large enough in order to conduct the SEM analyses, could be deemed by some as deficient in relation to the number of parameters that were estimated (Babbie & Mouton, 2001). Moreover, the positively skewed age distribution with a clear majority of respondents being aged 20 to 29 (43%) diminishes the generalisability of the study to the wider financial service seeking population. The educational distribution was negatively skewed with a larger proportion having obtained tertiary qualifications. According to Goodwin and Leech (2006) correlation coefficients are less if low variability exists among the observations of a variable. In relation to the interaction effects, the relatively concentrated sample in terms of *Age* and *Education* meant that the correlation coefficients may have been an underestimate of the correlation in the population. It is therefore recommended that future research studies attempt to utilise a larger, demographically diversified and representative sample.

Secondly, the study relied on the use of self-report questionnaires. This method of data collection carries many advantages. In relation to this study, where data was collected from a large pool of participants concurrently, advantages include practical, time related and cost efficiencies, as well as straightforward scoring and interpretation. That being said, however, this method carries an unavoidable element of risk. Self-report measures introduce the possibility of response bias, which refers to the tendency of a respondent to “systematically respond in a set or fixed manner to the item or question, thereby purposively presenting a skewed picture” (Foxcroft & Roodt, 2009, p. 50). There are several prevalent forms of response bias. Of specific relevance to this study, may be the presence of extremity, centrality and acquiescence bias. Extremity bias occurs when a respondent responds either very positively or very negatively, i.e. at the extreme ends of the rating scales. Centrality bias occurs when the respondents compress ratings around the midpoint of the scale. This may occur as a result of time constraint on the part of the respondent when wanting to complete the questionnaire quickly, with minimum thought and effort. Acquiescence bias occurs when the respondent systematically agrees with all of the statements or items. Somewhat related to this form of bias is the tendency to respond in a socially desirable way, i.e. the tendency to react in a manner that is seen as socially desirable or acceptable (Foxcroft & Roodt, 2009). In this instance, the respondent over-reports what is viewed as admirable characteristics or attributes and under-reports those attributes that are seen as less desirable or unacceptable, thereby creating a favourable impression of him or herself. Whether there was any incentive for respondents in this study to respond in this manner is questionable, but the possibility should nonetheless be considered when interpreting the results. The presence of response bias leads to erroneous conclusions about the reliability and validity of the instruments, and may artificially inflate or deflate the correlation between two constructs. The results of the study may thus not be a true reflection of the hypothesised effects, but rather a reflection of systematic response bias – evidently influencing the conclusions drawn from the results.

The third and greatest limitation pertains to shortcomings with regards to the reliability and validity of the measurement instruments utilised in this research. The quality of some of the measurement instruments used to operationalise some of the latent variables were called into question and to a certain extent eroded confidence in the success with which the indicator variables represented the latent variables in the structural model. More specifically, the low reliability scores attained by the *Neuroticism* and *Conscientiousness* subscales, and the mediocre CFA results produced by the Risk Tolerance Questionnaire (RTQ) (for the one factor model) should be highlighted. The RTQ posed the greatest challenge and results from the item and dimensionality analyses were not ideal. This could possibly be related to the fact that the measure consisted of variable scale points with as low as two response categories per item, the highest being four. The lower the number of response categories, the lower the expected reliability, validity and discriminatory power (Lee & Paek, 2014) when compared to instruments with more (e.g. four or five) response categories. This, however, was a limitation that was evident when the measurement was chosen and considered before the data analyses commenced. Nonetheless, a decision for using the RTQ was made for lack of a better public domain questionnaire. In addition, the RTQ was also deemed the most appropriate based on an investigation of the item content of the instrument. However, the effect of this decision probably played a significant role in the overall results, as *Risk-Tolerance* was the focal variable of the model and study. Overall, it could be argued that the rather poor reliability and validity of some of the measurement instruments possibly jeopardised the subsequent results obtained through SEM, thus attenuating the results to a rather dissatisfactory degree. The hypotheses formulated in chapter 2 were the result of systematic and comprehensive reasoning based on sound theoretical knowledge and previous research endeavours, and thus it is argued that a fair level of confidence, despite lack of significant relationships attained in the current study, could probably still be placed in the proposed model. More reliable and valid measurement of the problematic constructs could add considerable value in future research endeavours.

5.6 Practical Implications

The literature study presented in chapter 2 introduced a tentative four-quadrant grid according to which clients can be classified in terms of their *subjective risk judgment* (SRJ) and *objective risk-tolerance* (ORT) levels. It was argued that each client's unique combination of SRJ and ORT levels determines his/her overall level of *Client Risk-Tolerance*. In general, the higher both categories are, the higher the level of *Client Risk-Tolerance*. Similarly, lower scores within both categories would signal a lower level of *Client Risk-Tolerance*, whilst contrasting scores, e.g. low SRJ – high ORT or high SRJ – low ORT, would indicate moderate levels of *Client Risk-Tolerance*. It was argued, furthermore, that each of the four quadrants or categories are clearly distinguishable in terms of the individual characteristics and needs that comprise them, and each quadrant or profile warrants a different approach or action on the part of the financial advisor. The latter combinations require a carefully calculated and perceptual approach from the financial advisor in an attempt to reconcile the individuals' (subjective) willingness and (objective) ability to take risks.

The original grid depicted in figure 2.1 will serve to explain the practical value underlying the results obtained in this study. One of the central arguments set forth in this study is that *subjective risk judgment* variables in isolation have direct effects on *Client-Risk Tolerance*. Towards this end, SEM was used to test the hypothesised effects. Disappointingly, the SEM results revealed that only one of the hypothesised direct subjective effects, i.e. *Sensation Seeking* on *Risk-Tolerance*, and a single indirect subjective effect, i.e. *Extraversion* via *Sensation Seeking* on *Risk-Tolerance*, was found to be statistically significant. Nonetheless, these findings to a certain extent confirm the central argument of this study that *Client Risk-Tolerance* should not be interpreted to be merely a function of *objective risk-tolerance* factors, as *Sensation Seeking* and *Extraversion* seems to have a relatively strong influence on an individual's level of *Risk-Tolerance*. By taking cognisance of an individual's level of *Sensation Seeking* and *Extraversion*, the financial advisor could obtain a more accurate understanding or picture of the individual's *Risk-Tolerance* level. In doing so the financial advisor could improve his/her service provision and consequently, facilitate the selection of an investment portfolio that is optimal in terms of unique individual needs, and that resonates well with the individual's level of security and comfort.

An additional argument presented in this research holds that the subjective and objective risk-tolerance variables combine to influence *Risk-Tolerance*, and hence the formation of the four quadrant grid. The results produced by the moderated multiple regression analyses provides meaningful inferential power in terms of this grid. *Emotional Self-Management* and *Neuroticism* emerged as significant predictors of *Risk-Tolerance* when entered into a regression equation containing all individual difference factors (*subjective risk judgment* variables) and the hypothesised *Gender* interaction terms (*objective risk-tolerance* variables). The *Gender* x *Emotional Self-Management* interaction, and G*ender* x *Neuroticism* interaction effects statistically significantly explained unique variance in *Risk-Tolerance*. Thus, *Emotional Self-Management* and *Neuroticism* in isolation, as well as in complex dynamic interaction with *Gender* significantly influenced *Risk-Tolerance*.

Practically this indicates that different combinations of *Emotional Self-Management* and *Gender,* and *Neuroticism* and *Gender* would yield differing levels of *Client Risk-Tolerance* and would thus warrant different actions on the part of the financial advisor. More specifically, two individuals with the same standing on *Emotional Self-Management* and *Neuroticism* but who differ in terms of *Gender* will have quite differing levels of *Risk-Tolerance*. Therefore, *Gender* provides meaningful inferential significance when determining an individual's position in terms of *objective risk-tolerance* within the grid and will therefore, contribute to the determination of an individual's overall *Risk-Tolerance* level.

Two other variables that also hold significant inferential potential in terms of the grid are *Income* and *Education.* Both these *objective risk-tolerance* variables were found to moderate the relationship between *Emotional Self-Management* (*subjective risk-judgment* variable) and *Risk-Tolerance*, suggesting that the interaction of these *objective risk-tolerance* and *subjective risk judgment* variables will prove to be meaningful during the application of the grid to determine *Client Risk-Tolerance*. The results provided support for the argument that higher *Income* individuals (high ORT) with the superior ability to regulate emotions (high SRJ) have higher levels of *Client Risk-Tolerance* when compared to higher *Income* individuals (high ORT) with lower levels of *Emotional Self-Management* (low SRJ). The two combinations are characteristically different and would place the two individuals in the first and third quadrants respectively. Individuals with lower *Education* attainment (low ORT) and low *Emotional Self-Management* levels (low SRJ) would possess lower *Risk-Tolerance* levels versus those individuals with comparable levels of *Emotional Self-Management* but higher *Education* levels. In this instance the two characteristically unique individuals would be placed in quadrants four and two respectively. A refined grid based on these results is depicted in figure 5.1. The comprehensive grid clearly describes the individual characteristics and needs comprising each quadrant along with the appropriate actions that could be pursued by the financial advisor in order to provide quality service that is tailored to the unique needs of the client.

		HIGH ORT	LOW ORT
HIGH SRJ	DESCRIPTION	All aspects of this individual's profile point toward high levels of risk-tolerance. The individual is stimulated by the prospect of risk which he/she tends to view in a favourable light. A level of confidence in higher risk decisions with above average returns are displayed. Emotionally, he/she is not likely to display negative emotional reactions in relation to risk. This individual has a higher nominal amount to his/her disposal and it follows that he/she is better able to absorb financial loss and contribute additional financial capital should loss be sustained. A higher educational attainment enables the individual to perform a rational risk assessment. The individual is able to evaluate the risks inherent to the investment process. Rational calculations, statistical predictions as well as past financial experience and knowledge are used to establish the probabilities of return.	Risk is appraised as less threatening and more stimulating. This individual is not likely to ruminate over negative or anxiety provoking aspects of risk-taking. In spite of the greater preference for or willingness to take risk, he/she is limited by mediocre levels of income and education. This may jeopardise this individual's ability to bear risk, make optimal decisions and achieve investment objectives.
	ACTION	The individual should be encouraged to make high risk-high return investments.	This individual should be assisted to make more conservative investment choices, by means of a carefully calculated interpersonal approach that balances the advisor's technical expertise with individual's inherent preference for risk and stimulation.
LOW SRJ	DESCRIPTION	The individual is inherently risk averse. Risk is viewed as threatening and unstimulating and provokes a host of negative emotions such as anxiety. The individual is likely to be more sensitive to and ruminate over negative information and cues, impairing confidence and optimal decision-making. However, sufficient financial resources (to apportion to riskier financial decisions) and education (to allow rational risk assessment) will serve to buffer lower levels of emotional willingness or preference for risk. This individual is likely to take a methodical and calculated approach to financial decision-making.	This individual has a low preference for risky financial decisions. He/she is likely to appraise risk as threatening, does not derive much arousal/stimulation from engaging in risky financial decision-making and is likely to display lower levels of financial confidence. On an emotional level, this individual is likely to experience significant anxiety and/or related negative emotions when faced with risk. This is accompanied by a lower nominal amount to his/her disposal and an inability to absorb financial loss. Educational attainment is likely to be low and the individual lacks the ability to rationally evaluate risks inherent to the investment process. This individual is in need of greater financial security and support.
	ACTION	Moderately risky portfolios should be encouraged. This individual needs education and reassurance, by means of a carefully calculated and purposeful interpersonal approach that will enable more confident investment decision-making.	This individual requires broad spectrum financial education and advice services. Low volatility investments with limited potential for loss should be considered.

Figure 5.1. **Refined Client Risk-Tolerance profiles**

As a subsequent step, in response to the research results, the possibility exists to develop a psychometric measurement instrument aimed at assessing an individual's level of *Client Risk-Tolerance*. Such an instrument should utilise items that tap into the personality and emotion based constructs *Sensation Seeking*, *Extraversion*, *Neuroticism* and *Emotional Self-Management* as the results suggest that knowledge of certain aspects of personality and emotional regulation could aid the process of determining levels of *Client Risk-Tolerance*. However, here a great limitation is acknowledged in that financial advisors, by law, are not permitted to conduct such an assessment, as the assessment would constitute what is referred to as a psychological act. According to the Health Professions Act, Act 56 of 1974, measurement instruments that tap psychological constructs (such as personality[49]) may only be used, interpreted, and controlled by psychologists, or appropriately registered professionals other than psychologists, provided that the use of the test has been certified for that category of tester by the Psychometrics Committee of the Professional Board for Psychology (Health Professions Council of South Africa (HPCSA), 2006). Therefore, such an exercise would not be lucrative, as the advisor would have to rely on the expertise of an in-house psychologist or psychometrist to administer and interpret the responses.

Moreover, merely conducting such an assessment for the sake of determining *subjective risk judgment* (while certainly serving a value-adding function), does not fully embrace the potential practical function emanating from the research results. Such an assessment will only add real value if the financial advisor is able to utilise the results beyond the score that is obtained. More specifically, an assessment would add value if it enables the advisor to influence a client in such a way that an optimal decision is made based on the technical competence of the advisor, without neglecting the client's role in the decision making process.

At the core of this research lies the need to equip the advisor with a tool that will enable him or her to better understand the individual investor and to utilise this understanding to tailor his or her service provision in such a way, that a personalised service speaking to the needs of the client is rendered. In order to do this, the

[49] This would then apply to any measurement for *Sensation Seeking*, *Extraversion* and *Neuroticism*, but not for *Emotional Self-Management*.

financial advisor has to gain an understanding of the factors underlying subjective risk-tolerance specifically, the features of the significant individual difference factors as determined by this study, and the means of interacting with individuals that display different combinations of *objective risk-tolerance* and *subjective risk judgment* characteristics.

A practical solution would be to develop a behaviourally anchored rating scale (BARS) or a behavioural observation scale (BOS) – two variations of behavioural-based rating scales that can be used by the financial advisor to evaluate clients on the various significant predictors of *Client Risk-Tolerance*. The BARS is represented by different attributes or characteristics. Each characteristic is represented by a scale that is defined by concrete behavioural examples that reflect varying amounts or levels of the dimension under consideration (Debnath, Lee, & Tandon, 2015). Thus, instead of anchoring each dimension with numbers or single words, the BARS anchors dimensions with samples of specific behaviours applicable to the chosen context. The rater, i.e. the financial advisor, is tasked with choosing the behaviour most reflective of the individual in question.

The BOS contains a list of behaviours that are clustered to represent dimensions (e.g. *Sensation Seeking* and *Extraversion*). Instead of choosing the most appropriate behaviour, each behaviour in the cluster is assessed based on the frequency with which they occur. The extent to which an individual, i.e. the client, engages in each behaviour is usually rated on a multi-point scale ranging from “almost never” to “almost always”. The client’s score on each behavioural item is added to derive a total rating on each dimension. A higher score means that the client frequently engages in the stated behaviours, and a low score means that the client engages less or infrequently in the stated behaviours (Kleiman, n.d.). An example of a BOS applicable to the dimension of *Sensation Seeking* can be viewed in table 5.1. These two variants could be used to construct a structured behavioural interview guide, where the advisor is educated to recognise/probe and rate his/her clients in terms of a list of characterising statements; followed by an instructional guide facilitating the appropriate response action. This approach has potential in that behaviourally-based measures contain clear indicators that guide the advisor in his/her quest for ascertaining levels of *Risk-Tolerance*. Furthermore, the outputs of the BARS or BOS are directly linked to the context in which it is used, and therefore, by law, does not require expertise in psychological theory and application. The use of a BARS or BOS does, however, require that the user have specific expertise in this area of assessment.

Table 5.1

Example of a Behavioural Observation Scale for Investment Sensation Seeking

Investment Sensation Seeking	Almost Never				Almost Always
1. He/she has previously invested in high-risk options, such as stocks or commodities, and describes such investments as “exciting/ stimulating/thrilling”.	1	2	3	4	5
2. He/she has suffered a financial loss of 50%, or faced the prospect of suffering a similar loss, but was not really perturbed by this and will make a similar decision carrying the same probability of loss in future.	1	2	3	4	5
3. He/she does not avoid talking about “aggressive” (i.e. high risk - high return) investments.	1	2	3	4	5
Score 3-6 Low Investment Sensation Seeking 7-10 Medium Investment Sensation Seeking 11-15 High Investment Sensation Seeking					

This expertise would largely be dependent on the ability of the financial advisor to recognise the basic principles and behavioural manifestations of each construct. A basic understanding of the nature of the identified individual differences constructs on the part of the advisor would thus be critical. In the long run educational efforts should be geared towards improving future advisors’ understanding of the concept of *Investor Risk-Tolerance*, the various significant factors that underpin it, and the possible context specific manifestations of the various factors (as outlined in a BARS or BOS that would not require expertise in psychological theory and application).

5.7 Conclusion

The successful advisor is one who realises that an understanding of the individual he/she is dealing with is just as important as a thorough understanding of the technical aspects of investments and the basic nature of investment decision-making. Technical competence will remain quintessential to their service delivery. However, since there is no neatly packaged one-size fits all product, the service remains largely dynamic in nature – one that needs due consideration to each individual's personal circumstances and preferences.

The process of investing should be an empowering process – one where a technical decision is not made on behalf of the client, but in partnership with the client. The client should understand and appreciate the nature of an investment and the accompanying trade-off between risk and return. Thus, in all aspects of service delivery, the financial advisor should serve a counselling and supporting role. This implies transferring his/her technical knowledge through comprehensive financial education and a skilled approach to coaching or counselling that enables the client to make a decision that balances maximal gain (financially) with maximal security (emotionally). Clients should be encouraged to take the maximum amount of risk given their unique combination of objective and subjective characteristics. How the advisor goes about pursuing this topic requires a keen awareness and understanding of individual differences and emotions, and the ability to use this as a means of screening the client into the appropriate quadrant.

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APPENDIX A

UNIVERSITEIT•STELLENBOSCH•UNIVERSITY
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ORGANISATIONAL CONSENT FORM

Hereby I, ………………………………………………………………………………… (name and position) give Kate Swart (Master's student Stellenbosch University) permission to distribute questionnaires comprising the relevant measures for the purpose of generating data for her master's thesis (*The Development and Empirical Evaluation of a Client Risk-Tolerance Structural Model*) within ……………………………………………… (name of institution). The purpose of the study has been explained as well as the manner in which the data generated will be used.

……………………………………………………………………………….. (name and position) will be assisting in terms of the handing out as well as the collection of the questionnaires. The data will be collected anonymously and no reference to any individual respondents will be made.

Clients/investors will be rating themselves with informed consent on the following constructs:

- Personality (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism, sensation seeking, delay of gratification)
- Emotional Intelligence (emotional self-management and emotional self-control)
- Risk-Tolerance

Signed (please print name and sign): ____

Position in the participating organisation:____

Date: ___________________________________

APPENDIX B

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REQUEST TO MEASURE CLIENT/ INVESTOR RISK-TOLERANCE AND THE PREDICTORS THEREOF

Stellenbosch University has a goal to be an actively engaged university. It achieves this by continuously interacting with all stakeholders in its environment. The Department of Industrial Psychology functioning under the auspices of SU contribute to this mission. As a member of the department, I would like to take the liberty of asking permission to conduct research at your organisation, especially given your involvement in the financial services sector of South Africa and your existing client base of investors/ individuals seeking or receiving financial advice.

This research aims to provide valuable insight into the factors that predict client/investor risk-tolerance and to provide a better understanding of how individuals in South Africa make financial decisions. More specifically, the aim is to expand the investigation of variables that determine client/investor risk-tolerance beyond the testing of *objective risk-tolerance variables*, i.e. demographic and socioeconomic factors, to include the influence of what is termed *subjective risk judgment variables*, i.e. personality and emotion regulation, on client risk-tolerance in isolation, as well as in a complex dynamic interaction with each other to determine more comprehensive client risk profiles. This will be done in an attempt to increase the effectiveness of the financial advisor's service provision.

The study will specifically investigate the effect of the following variables on client/investor risk-tolerance: *extraversion, conscientiousness, openness to experience, agreeableness*, *neuroticism, sensation seeking, delay of gratification, emotional self-management* and *emotional self-control* (as subjective risk judgment variables); and *age, gender, income* and *education* (as objective risk-tolerance variables). For a more thorough description of the proposed study, please consult the attached research proposal. By participating in the proposed study, the following will be required:

1. This study needs the participation of clients/ investors seeking, or already receiving, financial advice or assistance.
2. This study further requires financial advisors that are willing to distribute the attached questionnaire to their clients/ investors, as the researcher is aware of the fact that financial institutions are not allowed to provide the names and contact details of clients to outside parties.
3. The questionnaire does not have a time limit, but should take each client approximately 40 minutes to complete.

With your permission, the researcher will provide you with hard copy questionnaires. You will be requested to ask your clients to fill out the questionnaire and give it back to you. The researcher will collect the completed questionnaires from your organisation at a time, date and location of your choice.

This research study aims to contribute to the academic field of the investigated area, and your contribution would be of great importance to achieving this goal. All data sources will be treated as confidential and would be used for research purposes only. The data will be collected anonymously and no reference to any individual respondents or your organisation will be made. A process of ethical clearance for this project is underway, and the outcomes thereof will be submitted to you before any participation will be required. Pending your approval, I kindly request to undertake this study during the months May to July 2015. If you consent to participate (i.e. by distributing the questionnaires to your clients), please complete the attached consent form and e-mail it to the researcher (K Swart; 16164105@sun.ac.za). Your involvement, help and participation will be greatly appreciated.

Yours sincerely,
Kate Swart & Dr Gina Görgens

APPENDIX C

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STELLENBOSCH UNIVERSITY

CONSENT TO PARTICIPATE IN RESEARCH

The Research Project: **The Development and Empirical Evaluation of a Client Risk-Tolerance Structural Model.**

Form addressed to: **Individual investor seeking financial advice at a financial institution.**

You are asked to participate in a research study conducted by Kate Swart (master's student, MComm) and Dr Gina Görgens, from the Department of Industrial Psychology at Stellenbosch University. The results of this study will contribute to the thesis of Kate Swart. You were selected as a possible participant in this study because you are an individual investor seeking financial advice at a financial institution.

1. PURPOSE OF THE STUDY

This research aims to provide valuable insight into the factors that predict client/investor risk-tolerance and to provide a better understanding of how individuals in South Africa make financial decisions. More specifically, the aim is to expand the investigation of variables that determine client/investor risk-tolerance beyond the testing of *objective risk-tolerance variables*, i.e. demographic and socioeconomic factors, to include the influence of what is termed *subjective risk judgment variables*, i.e. personality and emotion regulation, on client risk-tolerance in isolation, as well as in a complex dynamic interaction with each other to determine more comprehensive client risk profiles. This will be done in an attempt to increase the effectiveness of the financial advisor's service provision.

2. PROCEDURES

If you volunteer to participate in this study, we would ask you to complete a self assessment questionnaire with a duration of approximately 40 minutes.

3. POTENTIAL RISKS AND DISCOMFORTS

Potential risks and/or discomforts that could result from participating in this study include the time that is required to fill out the questionnaire and the potential discomfort of having to disclose the sensitive information of the salary bracket you fall in. If you decide to participate in the study, please be informed that you are allowed to withdraw participation at any time prior to, during, or after the study.

4. POTENTIAL BENEFITS TO SUBJECTS AND/OR TO SOCIETY

There exist no direct benefits for you. However, the development of a client risk-tolerance structural model will assist in the development of interventions aimed at enhancing the effectiveness of financial advisor service provision, thereby contributing to the financial sector, the economy and society as a whole.

5. PAYMENT FOR PARTICIPATION

No payment will be awarded for participating in the research study.

6. CONFIDENTIALITY

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. Confidentiality will be maintained by restricting access to the data to the researchers (Kate Swart and Dr Gina Görgens), by storing the data on a password-protected computer, and by only reporting aggregate statistics of the sample. The results of this study will be distributed in an unrestricted electronic thesis, as well as an article published in an accredited scientific journal. The publications will not reveal the identity of any research participant, or any of the individual findings obtained through the various questionnaires.

7. PARTICIPATION AND WITHDRAWAL

You can choose whether to participate in this study or not. If you volunteer to participate in this study, you may withdraw at any time without suffering any consequences. You may also refuse to answer any questions that you do not wish to answer and still remain in the study. The investigator may withdraw you from this research if circumstances arise which warrant doing so.

8. IDENTIFICATION OF INVESTIGATORS

If you have any questions or concerns regarding the research study, please feel free to contact Kate Swart [16164105@sun.ac.za; 074 473 9307] or Dr Gina Görgens [ekermans@sun.ac.za; 021 808 3596].

9. RIGHTS OF RESEARCH SUBJECTS

You may withdraw your consent at any time and discontinue participation without penalty. You are not waiving any legal claims, rights or remedies because of your participation in this research study. If you have questions regarding your rights as a research subject, contact Ms Maléne Fouché [mfouche@sun.ac.za; 021 808 4622] at the Division for Research Development at the University of Stellenbosch.

CONSENT FORM (please tick the appropriate box):	
I hereby consent to voluntarily participate in this study. I agree that my data can be integrated into a summary of the results of all the questionnaires without identifying me personally.	☐
	☐

I don’t want to participate in this study.
APPENDIX D

CLIENT/INVESTOR RISK-TOLERANCE

QUESTIONNAIRE

Self Assessment Form

Confidential*

* Your response to this questionnaire is completely confidential

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CONSENT TO PARTICIPATE IN RESEARCH

The Research Project: **The Development and Empirical Evaluation of a Client Risk-Tolerance Structural Model.**

Form addressed to: **Individual investor seeking financial advice at a financial institution.**

You are asked to participate in a research study conducted by Kate Swart (master's student, MComm) and Dr Gina Görgens, from the Department of Industrial Psychology at Stellenbosch University. The results of this study will contribute to the thesis of Kate Swart. You were selected as a possible participant in this study because you are an individual investor seeking financial advice at a financial institution.

1. PURPOSE OF THE STUDY

This research aims to provide valuable insight into the factors that predict client/investor risk-tolerance and to provide a better understanding of how individuals in South Africa make financial decisions. More specifically, the aim is to expand the investigation of variables that determine client/investor risk-tolerance beyond the testing of *objective risk-tolerance variables*, i.e. demographic and socioeconomic factors, to include the influence of what is termed *subjective risk judgment variables*, i.e. personality and emotion regulation, on client risk-tolerance in isolation, as well as in a complex dynamic interaction with each other to determine more comprehensive client risk profiles. This will be done in an attempt to increase the effectiveness of the financial advisor's service provision.

2. PROCEDURES

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CONSENT FORM (please tick the appropriate box):	
I hereby consent to voluntarily participate in this study. I agree that my data can be integrated into a summary of the results of all the questionnaires without identifying me personally.	☐
I don't want to participate in this study.	☐

INSTRUCTIONS

Please read the following general instructions carefully:

[1] This questionnaire is not a test.

[2] No right or wrong answers are possible.

[3] Please answer **ALL** of the questions.

[4] Choose only **ONE** answer.

[5] There is no time limit to complete the questionnaire. You should however try to complete the questionnaire within 40 minutes.

[6] Answer all the questions as truthfully and honestly as possible

[7] Upon completion, please return this questionnaire to your financial advisor/institution.

SECTION 1: DEMOGRAPHIC AND SOCIOECONOMIC DETAILS			
AGE		**GENDER**	
EDUCATION			
What is your highest level of education? Please mark with an ✗			
	Doctorate		Higher Certificate/ Advanced National (vocational) Certificate
	Masters Degree		Grade 12 (National Senior Certificate)
	Honours Degree/ Post Graduate Diploma		Grade 11
	Bachelor's Degree/ Advanced Diploma		Grade 10
	Diploma/ Advanced Certificate		Grade 9
INCOME			
What is your approximate annual gross income before taxes? Please mark with an ✗			
	R0-R54 344 per annum		R631 121-R863 906 per annum
	R54 345-R151 727 per annum		R863 907-R1 329 844 per annum
	R151 728-R363 930 per annum		R1 329 845+ per annum
	R363 931-R631 120 per annum		

PLEASE TURN TO THE NEXT PAGE

On the following pages, there are phrases describing people's behaviors. Please use the rating scale of each measure to describe how accurately each statement describes you. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence. Please read each statement carefully, and then circle the number that corresponds to the rating on the scale.

NB: Please note that there are four different scales in the questionnaire. Please consider each scale carefully before answering the questions.

SECTION 2	**Very Inaccurate**	**Moderately Inaccurate**	**Neither Inaccurate nor Accurate**	**Moderately Accurate**	**Very Accurate**
1. I am the life of the party.	1	2	3	4	5
2. I sympathize with others' feelings.	1	2	3	4	5
3. I get chores done right away.	1	2	3	4	5
4. I have frequent mood swings.	1	2	3	4	5
5. I have a vivid imagination.	1	2	3	4	5
6. I don't talk a lot.	1	2	3	4	5
7. I am not interested in other people's problems.	1	2	3	4	5
8. I often forget to put things back in their proper place.	1	2	3	4	5
9. I am relaxed most of the time.	1	2	3	4	5
10. I am not interested in abstract ideas.	1	2	3	4	5
11. I talk to a lot of different people at parties.	1	2	3	4	5
12. I feel others' emotions.	1	2	3	4	5
13. I like order.	1	2	3	4	5

CONTINUED…

PLEASE TURN TO NEXT PAGE

14. I get upset easily.	1	2	3	4	5
15. I have difficulty understanding abstract ideas.	1	2	3	4	5
16. I keep in the background.	1	2	3	4	5
17. I am not really interested in others.	1	2	3	4	5
18. I make a mess of things.	1	2	3	4	5
19. I seldom feel blue.	1	2	3	4	5
20. I do not have a good imagination.	1	2	3	4	5

SECTION 3	**Strongly Disagree**	**Disagree**	**Neither Disagree nor Agree**	**Agree**	**Strongly Agree**
1. I would like to explore strange places.	1	2	3	4	5
2. I get restless when I spend too much time at home.	1	2	3	4	5
3. I like to do frightening things.	1	2	3	4	5
4. I like wild parties.	1	2	3	4	5
5. I would like to take off on a trip with no pre-planned routes or timetables.	1	2	3	4	5
6. I prefer friends who are excitingly unpredictable.	1	2	3	4	5
7. I would like to try bungee jumping.	1	2	3	4	5
8. I would love to have new and exciting experiences, even if they are illegal.	1	2	3	4	5

PLEASE TURN TO NEXT PAGE

SECTION 4	Almost Never	Seldom	Sometimes	Usually	Almost Always
1. I take criticism from colleagues personally.	1	2	3	4	5
2. I demonstrate enthusiasm appropriately at work.	1	2	3	4	5
3. I remain focused when anxious about something at work.	1	2	3	4	5
4. I engage in activities that make me feel positive at work.	1	2	3	4	5
5. I behave inappropriately when angry at work.	1	2	3	4	5
6. I ruminate about things that anger me at work.	1	2	3	4	5
7. I demonstrate excitement at work appropriately.	1	2	3	4	5
8. When I am under stress I become impulsive.	1	2	3	4	5
9. I effectively deal with things that annoy me at work.	1	2	3	4	5
10. I fail to control my temper at work.	1	2	3	4	5
11. I appropriately respond to colleagues who frustrate me at work.	1	2	3	4	5
12. I hold back my initial reaction when something upsets me at work.	1	2	3	4	5
13. I demonstrate positive moods and emotions at work.	1	2	3	4	5
14. I am impatient when things don't get done as planned at work.	1	2	3	4	5
15. I quickly adjust to new conditions at work.	1	2	3	4	5
16. When upset at work I still think clearly.	1	2	3	4	5
17. I fail to handle stressful situations at work effectively.	1	2	3	4	5
18. I respond to events that frustrate me appropriately.	1	2	3	4	5
19. I fail to keep calm in difficult situations at work.	1	2	3	4	5
20. I explore the causes of things that upset me at work.	1	2	3	4	5

PLEASE TURN TO NEXT PAGE

SECTION 5	**Strongly Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Strongly Agree**
1. When I am able to, I try to save away a little money in case an emergency should arise	1	2	3	4	5
2. It is hard for me to resist buying things I cannot afford.	1	2	3	4	5
3. I try to spend my money wisely.	1	2	3	4	5
4. I cannot be trusted with money.	1	2	3	4	5
5. When someone gives me money, I prefer to spend it right away.	1	2	3	4	5
6. I manage my money well.	1	2	3	4	5
7. I enjoy spending money the moment I get it.	1	2	3	4	5

PLEASE TURN TO NEXT PAGE

For the next section please fill in the appropriate response circles.

SECTION 6

1. In general, how would your best friend describe you as a risk taker?

- ◯ A real gambler
- ◯ Willing to take risks after completing adequate research
- ◯ Cautious
- ◯ A real risk avoider

2. You are on a TV game show and can choose one of the following. Which would you take?

- ◯ R10 000 in cash
- ◯ A 50% chance at winning R50 000
- ◯ A 25% chance at winning R100 000
- ◯ A 5% chance at winning R1 000 000

3. You have just finished saving for a "once-in-a-lifetime" vacation. Three weeks before you plan to leave, you lose your job. You would:

- ◯ Cancel the vacation
- ◯ Take a much more modest vacation
- ◯ Go as scheduled, reasoning that you need the time to prepare for a job search
- ◯ Extend your vacation, because this might be your last chance to go first-class

4. If you unexpectedly received R200 000 to invest, what would you do?

- ◯ Deposit it in a bank account, money market account, or an insured CD
- ◯ Invest it in safe high-quality bonds or bond mutual funds
- ◯ Invest it in stocks or stock mutual funds

5. In terms of experience, how comfortable are you investing in stocks or stock mutual funds?

- ◯ Not at all comfortable
- ◯ Somewhat comfortable
- ◯ Very comfortable

CONTINUED…

PLEASE TURN TO NEXT PAGE

6. When you think of the word "risk", which of the following words comes to mind first?

- ◯ Loss
- ◯ Uncertainty
- ◯ Opportunity
- ◯ Thrill

7. Some experts are predicting prices of assets such as gold, jewels, collectibles, and real estate (hard assets) to increase in value. Bond prices may fall; however, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high interest government bonds. What would you do?

- ◯ Hold the bonds
- ◯ Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets
- ◯ Sell the bonds and put the total proceeds into hard assets
- ◯ Sell the bonds, put all the money into hard assets, and borrow additional money to buy more

8. Given the best and worst case returns of the four investment choices below, which would you prefer?

- ◯ R2 000 gain best case; R0 gain/loss worst case
- ◯ R8 000 gain best case; R2 000 loss worst case
- ◯ R26 000 gain best case; R8 000 loss worst case
- ◯ R48 000 gain best case; R24 000 loss worst case

9. In addition to whatever you own, you have been given R10 000. You are now asked to choose between:

- ◯ A sure gain of R5 000
- ◯ A 50% chance to gain R10 000 and a 50% chance to gain nothing

CONTINUED…

PLEASE TURN TO NEXT PAGE

10. In addition to whatever you own, you have been given R20 000. You are now asked to choose between:

- ◯ A sure loss of R5 000
- ◯ A 50% chance to lose R10 000 and a 50% chance to lose nothing

11. Suppose a relative left you an inheritance of R1 000 000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?

- ◯ A savings account or money market mutual fund
- ◯ A mutual fund that owns stocks and bonds
- ◯ A portfolio of 15 common stocks
- ◯ Commodities like gold, silver, and oil

12. If you had to invest R200 000, which of the following investment choices would you find most appealing?

- ◯ 60% in low-risk investments, 30% in medium-risk investments, 10% in high-risk investments
- ◯ 30% in low-risk investments, 40% in medium-risk investments, 30% in high-risk investments
- ◯ 10% in low-risk investments, 40% in medium-risk investments, 50% in high-risk investments

13. Your trusted friend and neighbour, an experienced geologist, is putting together a group of investors to fund an exploratory gold mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?

- ◯ Nothing
- ◯ One month’s salary
- ◯ Three month’s salary
- ◯ Six month’s salary

End of Questionnaire: Please hand this questionnaire in to your financial advisor.
Thank you for participating in the current research study.